

**Application of Mathematical Methods in the Study of Chemical Dynamical
Systems to an Inventory Multiplier-Accelerator Model**

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Abstract

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1. Introduction

The study of dynamical systems is traditionally thought to have begun with the publication of "New methods of Celestial Mechanics" by Poincaré and expanded with the work of Lyapunov into a theory of the stability of dynamical systems. It was not until the 1960s however that the use of chaos and stability theory exploded across disciplines.¹

Dynamics are typically an unnecessary tool when studying the paths of chemical reactions. Their value became apparent however, when Belousov and later Zhabotinsky released published their work on an oscillatory reaction, a reaction that would later come to be known as the BZ reaction.² Cycles were also known to exist in the biochemical realm with many famous pathways in organisms such as the Krebs cycle and Calvin cycle; however the BZ reaction was developed to create an inorganic analogue to the Krebs cycle.³ The development of this cycle allowed for a relatively easily replicable cyclic reaction with with easily measurable indicators of the progress of the reaction.

The study of dynamical chemical systems has since expanded to a variety of other mechanisms such as self-replicating molecules⁴ in addition to studying fractal patterns and dimensionality involved in electrochemical deposits⁵ and flame patterns.⁶ Despite the fairly wide range of background information required to set up these different models, the underlying mathematical theory used to study these models is identical which has contributed to the wide range of interdisciplinary work performed by theorists in the field.

1.1 Background on Dynamical Systems

Traditional dynamical systems are modelled in continuous time as a system of ordinary differential equations. These systems typically treat time as the singular independent variable and solve for the evolution of one or more variables in terms of time. A classic continuous time dynamical system is the simple pendulum which allows one to model the movement of a pendulum in space in terms of time. This model uses a variety of simplifying assumptions in order to reduce the problem of the pendulum into a single variable function, holding the length of the pendulum and acceleration due to gravity

constant.

$$\frac{d^2}{dt^2} + \frac{g}{L} \sin \theta = 0 \quad (1.1)$$

Most attempts at modelling real-world systems however require the use of multiple dependent variables in order to effectively model. However, as the amount of variables increases, the complexity of the model increases. Modelling an n -body system acting on each other gravitationally is of obvious interest in astronomy; however, it was quickly found that although a 1 and 2 body system were relatively simple to solve for, the introduction of a third body caused significant complications. The 3-body system is in fact what Poincaré studied in order to develop a theory of chaotic deterministic systems.⁷

That is not to say that these systems cannot arrive at ordered solutions. Although continuous time systems require a minimum of 3 variables in order for chaos to arise, there are typically windows of order in chaotic regimes that allow for stable, oscillatory behavior. The BZ-reaction is still being actively studied and is known to be actually highly complex but is often reduced into 7 primary sub-reactions.³ A great deal of the work involved in studying dynamical systems is actually on finding ways to simplify models in order to arrive at more mathematically tractable systems. The BZ-reaction has been simplified to a 3-variable system that still provides the complex periodicity and chaotic behavior characteristic of the model.⁸

Although many processes in the real-world are more intuitively interpreted as operating as a continuous time function, there are many occasions where it is possible and in fact beneficial to think in a discrete-time sense. The prevalence of this type of system varies depending on the exact field of study; however, it is important to note that when computationally modelling continuous time systems, it is impossible for computers to truly operate with continuous variables and thus even these systems are reduced to technically discrete models.

Population dynamics are frequently analyzed as a discrete time system as opposed to continuous time. It is often of more practical use to interpret $t = 0, 1, 2, 3, \dots$ as the change in population per year or per season as opposed to determining the change in population over infinitesimally small changes in time. In terms of technique, many of the mathematical principles used in analyzing dynamic systems in continuous time apply to discrete time systems; however, it would be a mistake to assume the two were identical. An important distinction between the two is the nature by which chaos can occur. As described previously, a continuous time system requires 3 or more dependent variables in order for chaos to occur. A discrete time system only requires 1 variable in order to display the same type of chaotic behavior.

The systems discussed throughout this paper will be of the discrete variety due to

their nature. Laws pertaining to the physical world are scalable to the infinitesimal degree which allows for their use in continuous models. Economic models do not have a basis in physical laws. It is also important to note that, due to the complexity involved in the human behavior that economic models are trying predict, the exact numerical values of the model are typically of minor concern. The general behavior of the model is significantly more valuable in order to determine the effects of an economic assumption.

The logistic map is regarded as the prototypical chaotic discrete time mapping. The logistic function, which the logistic map is based off of, was developed to study population dynamics but actually garnered widespread use in other disciplines such as the study of autocatalytic reactions, computer science, statistics, and economics.⁹

$$\frac{d}{dx}f(x) = f(x)(1 - f(x)) \quad (1.2)$$

The logistic function has 2 equilibria or points where the derivative of the function is 0. $f(x) = 0$ is an unstable equilibrium but $f(x) = 1$ is a stable equilibrium point which means that other points on the function will tend towards this equilibrium overtime. This can be realized by solving for the derivative of the function at points when $f(x) \in (0, 1)$ which is universally positive and $f(x) \in (1, \infty)$ which is negative. Integrating the differential equation gives the general form equation:

$$f(x) = \frac{e^x}{e^x + C} \quad (1.3)$$

This function gained prominence due to its rapid, exponential growth when $f(x)$ is low and its slow, linear decaying to non-existent growth as population increases. Used by notable mathematicians operating in the field of population dynamics such as Verhulst, Pearl, and Lotka, the model continues to be widely used today and is often the basis upon which other modifications are applied.¹⁰

$$x_{t=1} = \mu x_t(1 - x_t) \quad (1.4)$$

The logistic map is a difference equation model popularized by Robert May as a discrete time analogue to the logistic function.¹¹ When interpreted in the biological context, x_t refers to the ratio of the population at time t compared to the maximal population, thus the mapping is bounded between 0 and 1. Here we see intuitively the major difference between difference equation and differential equation based systems. Differential equations solve for the derivative of a variable with respect to time in terms of the variable, difference equations solve for the actual state of the variable in the successive state provided we know

the state of the variable in the previous time period. Much like how differential equations can be of higher order with the introduction higher order derivatives, a difference equation can also be of higher order by including more time periods in the function for the state of the variable which is valuable in a variety of the models discussed later.

Much like how the equilibrium points were solved for in the differential equation, difference equations also have equilibrium points where $x_{t+1} = x_t$. Interestingly, unlike the logistic function, there does not exist a fixed point at $x_t = 1$ as this would result in $x_{t+1} = 0$. Solving for the fixed points, we have:

$$x_{t+1} = x_t = 0, \frac{\mu - 1}{\mu} \quad (1.5)$$

The stability of a fixed point is again dependent on the derivative of the function; however, there are differences in the details of our analysis. Treating $f(x) = x_{t+1}$, we see the derivative of the logistic map is:

$$f'(x) = \mu(1 - 2x) \quad (1.6)$$

For reasons that will become clear later, the stability of a point on the map requires that $|f'(x)| < 1$. Solving for when this is true for our two fixed points, we see that $\mu < 1$ provides stability for the origin fixed point and $1 < \mu < 3$ gives stability for the non-zero fixed point. Thus, provided the parameter μ satisfies either of the conditions set previously, it will converge to one of the fixed points in a relatively small, finite amount of iterations.

This behavior can be visualized using a cobweb diagram. This diagram consists of 3 primary elements: a plot of the mapping, a 45° line, and a plot of the variable's trajectory. An example of a cobweb diagram can be seen in Figure 1.1. This diagram shows the trajectory of x starting at a value of 0.1 when there is a stable, non-trivial fixed point.

The 45° line is defined as the line where $x_t = x_{t+1}$ which is useful for determining the result of successive iterations. Beginning from the point x_0 , we can then determine what point x_1 will be via the mapping. We can then look horizontally to the 45° line until we intersect with it. The x -coordinate of this intersection point is equivalent to the result of the mapping of the previous iteration, thus using this new point will allow us to determine the result of the next iteration of the function. This process can be repeated ad infinitum; however, the result will soon prove uninteresting for stable points and orbits as the trajectory will converge and repeat its behavior.

The reason the logistic map is so frequently studied is because of its ability to exhibit

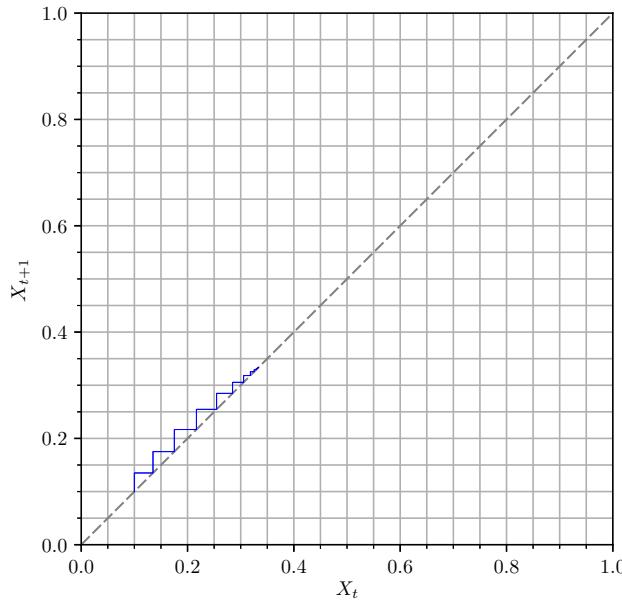


Figure 1.1: Cobweb plot of the logistic map setting $\mu = 1.5$ and $x_0 = 0.1$. The trajectory asymptotically approaches the equilibrium point of $\frac{1}{3}$.

complex behavior beyond a stable equilibrium solution. Once $\mu > 3$, the mapping enters a cyclic region. Much like how fixed points could be solved for by identifying where $x_t = x_{t+1}$, stable oscillatory points can be found by solving for the equilibrium points of higher iterations of the function. A 2-cycle will be such that $x_t = x_{t+2} \neq x_{t+1}$ for example and the stability of a such a cycle can be found using the same methodology as described previously. The logistic map also provides a mechanism to more quantitatively describe what it means for a system to be chaotic. The Lyapunov exponent, named after one of major driving forces in the development of stability analysis, is used to measure the effect of small perturbations in initial conditions on the trajectory of the variable.¹² Conceptually, the logistic map and the systems discussed in this paper are deterministic. However, chaotic systems have highly divergent trajectories with even small changes in their initial conditions; thus knowing approximately what the initial conditions are does not provide approximate information on the trajectory of the variable.

In order to quantify this, we begin by taking the absolute value of the derivative of the function as this allows us to effectively magnify the effect of an infinitesimal change in the initial conditions. We then take the natural logarithm of this derivative in order to measure the exponential rate of separation of trajectories. Finally, we take the average separation over an arbitrarily high number of iterations n as exponential separation is

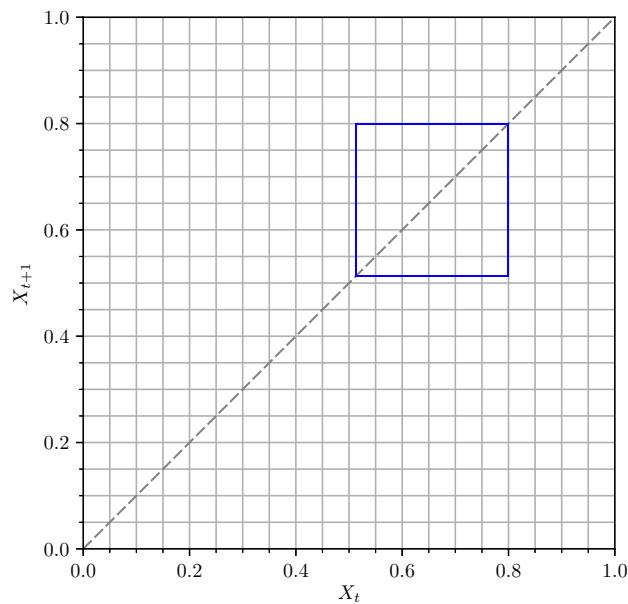


Figure 1.2: 2-period cycle of the logistic map showing only the cyclic behavior.

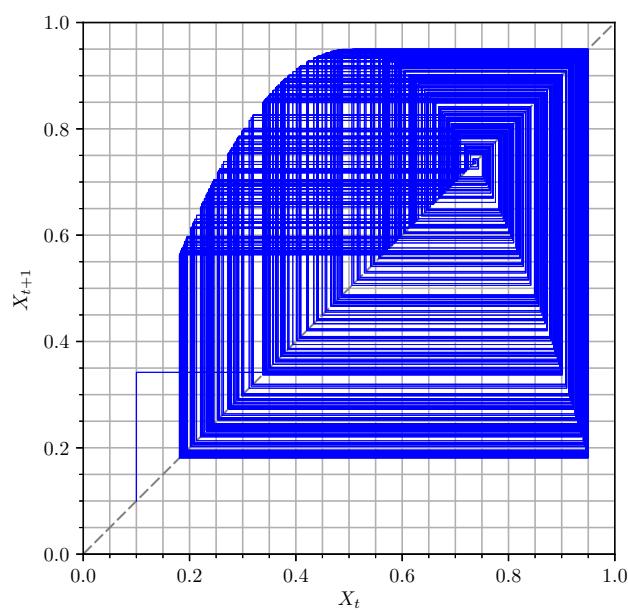


Figure 1.3: Chaotic behavior in the logistic map.

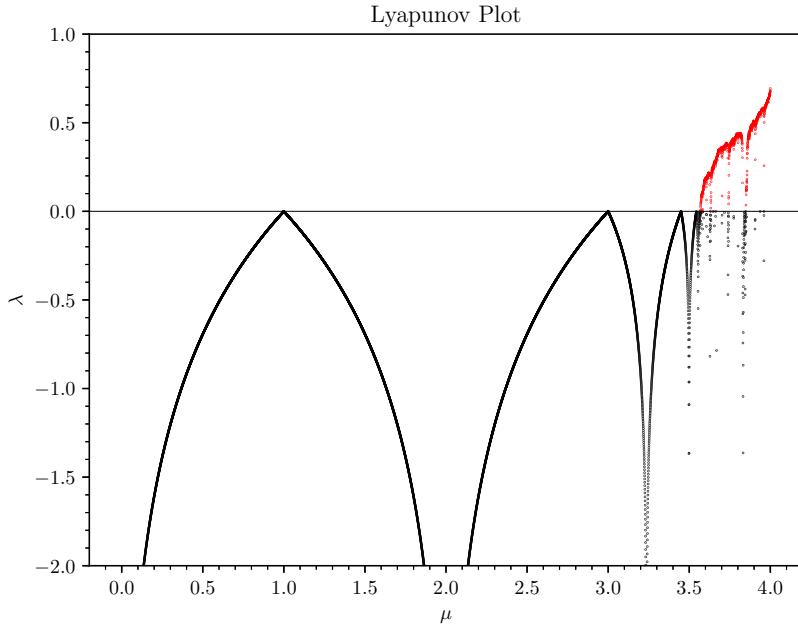


Figure 1.4: Lyapunov exponent plotted against μ for the logistic map. Initial value of 0.1 is used. Red denotes regions where $\lambda \geq 0$, black denotes regions where $\lambda < 0$.

not necessitated over all phase space. This gives us the equation:

$$\lambda_n(x_0) = \frac{1}{n} \sum_{t=1}^{t=n} \ln|f'(x_{t-1})| \quad (1.7)$$

where $\lambda_n(x_0)$ is the lyapunov exponent for a given initial point when allowed to run for n iterations. The true value of the lyapunov exponent is the limit of the infinite series as $n \rightarrow \infty$ divided by n ; however, the complexity of these maps often makes it practically impossible to analytically solve for the limit. By choosing arbitrarily high values of n though, it is possible to achieve better approximations at the expense of computational time. It is also important to note that, although the lyapunov exponent is a function of the initial condition, as long as the initial state is not in some stable fixed point or cycle, the trajectories will follow that of the chaotic attractor, thus the value of the lyapunov exponent should be mostly consistent regardless of the choice of initial conditions.

Another way visually see the behavior is with a bifurcation diagram. This diagram shows the longterm behavior of the variable for a given variable. Figure 1.5 qualitatively shows the behavior described previously. For parameter values between 0 and 1, we see the origin fixed point is stable. For parameter values between 1 and 3, their is still a single fixed point that is monotonically increasing; however, we can also clearly see the

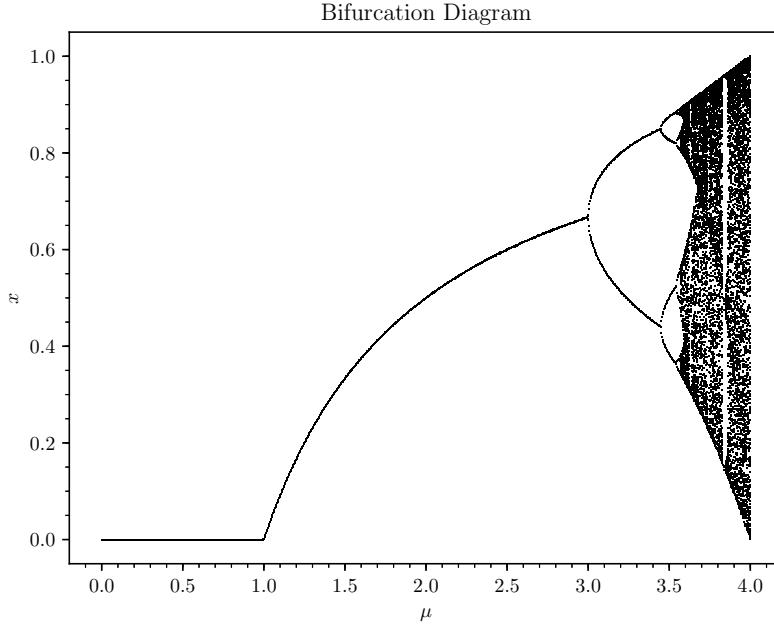


Figure 1.5: Bifurcation diagram plotting x against μ for the logistic map.

beginning of the 2-period cycle once the parameter exceeds 3. It is difficult however, to determine when predictable higher-order cyclic behavior ends and chaotic behavior begins via qualitative observation of the bifurcation diagram. The benefit of the bifurcation diagram is that it allows us to see both where the bifurcation points are and what behavior the bifurcation points signify. Bifurcation points are where infinitesimally small quantitative changes in the parameter induce significant qualitative or topological change in the behavior of the mapping such as the transition from a stable fixed point to a 2-period cycle.

Research on the logistic map and other iterated maps has shown the existence of what is called Feigenbaum's constant. This constant can be found by observing the behavior of the periodic cycles of the map. The interval of stability decreases and the ratio of subsequence intervals actually approaches a limit $\delta \approx 4.6692$.¹² All other topologically similar maps with a single local maximum share this Feigenbaum constant. Once the mapping exceeds this constant, chaos occurs which allows for another method to determine precisely where chaotic behavior occurs.

It is also beneficial to point out that another mechanism exists for cyclic behavior to exist. The previously described method involved taking a mapping and solving for the stability of its double iteration. This allows for $2n$ -period stability cycles to exist. However, there does exist odd-ordered cycles such as the 3 cycle; however, it occurs as a

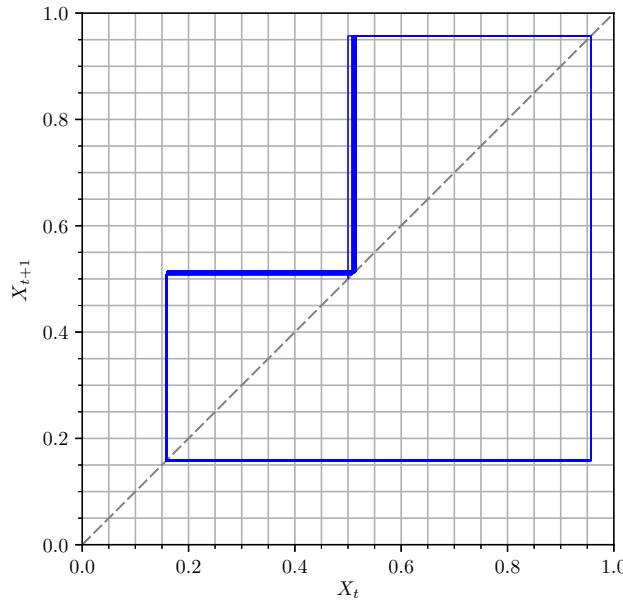


Figure 1.6: 3-period cycle of the logistic map showing only the cyclic behavior.

window of order in the region of chaos. These windows can be seen in Figure 1.4 where the Lyapunov exponent dips into the negative region past the chaotic bifurcation point. These bifurcation points are known as tangent bifurcations. This also allows us to use Sharkovsky's Theorem, which states that any continuous mapping with a 3-period cycle must also have every n -period cycle for every $n \in \mathbb{Z}$.¹² A variety of other mathematical techniques exist to study the dynamics of difference equation mappings but these will be covered more specifically when used for the specific case.

2. Heterogenous Inventory Cycles by Westerhoff et al.

2.1 Background

John Maynard Keynes work revolutionized economic thought; however, he never formalized any of his theories into a mathematical theory. This was performed in a process known as the neoclassical synthesis which was so called for its attempt to bridge classical models with these Keynesian principles. Although nobel prize winning Paul Samuelson was widely credited with providing a mathematical basis to Keynesian economics and popularizing the neoclassical synthesis, he was far from the only economist involved in the movement^{13,14}

Another notable Keynesian was Lloyd Metzler who developed a type of multiplier-accelerator business cycle. This type of model allows for cyclic behavior to occur endogenously, that is to say the model allows for persistent behavior outside of the steady state. This idea runs contrary to the idea that economic booms and recessions are reactions to exogenous shocks which is common in the new classical models. Also known as freshwater economics, these models assume that agents are perfectly rational and are capable of learning from past experiences. This viewpoint came into prominence in the late 1970s with a model by Lucas and Sargent¹⁵ which sought to move past these seemingly outdated Keynesian principles. In the modern day however, Keynesianism has regained popularity with a new neoclassical synthesis that resulted in a new school of thought, New Keynesianism, that seeks to provide stronger microfoundations to macroeconomic models than was previously encountered in neo-Keynesianism.

Many models developed in the neo-Keynesian era of economics still remain in use but have either been expanded or used to study specific relationships. Wegener, Westerhoff, and Zaklan expand upon Metzler's inventory cycle model by introducing heterogenous expectations into firm behavior.¹⁶

Unlike the well known multiplier-accelerator model developed by Samuelson and Hicks, the dynamics of this model are driven by shifts in the heterogenous mix of behaviors in the firms. This model reduces the decision of firms to one of two behaviors, a regressive

type and an extrapolative type. The extrapolative behavior occurs when a firm predicts that future income will deviate from the long-run average. The regressive behavior occurs when firms predict that future income will return to the long-run average. It is this heterogeneity as well as the ability for firms to switch their behavior type that is the defining feature of this model.

2.2 Model Set-Up

In this business cycle model, the economy is closed and income is determined completely by the quantity of goods produced by firms. Goods are completely homogenized but can be produced for 3 purposes: stock S , consumption U , and investment I . This lets us define income as:

$$Y_t = I_t + S_t + U_t \quad (2.1)$$

Investment is held to be exogenously determined and constant, thus:

$$I_t = \bar{I} \quad (2.2)$$

Consumption adapts to income according to the marginal propensity to consume, b . As this model follows closely to the framework developed by Metzler,¹⁷ consumption adapts directly to the current income level as follows:

$$C_t = bY_t \quad (2.3)$$

Producers have a desired level of inventory based on the expected level of consumption goods. Thus setting, $k > 0$:

$$\hat{Q}_t = kU_t \quad (2.4)$$

where Q is the level of inventory. In order to achieve this desired level of inventory, firms produce S amount of output such that:

$$S_t = \hat{Q}_t - Q_{t-1} \quad (2.5)$$

However, the expected level of consumption does not necessarily match the produced level of goods. The realized level of inventory change can thus be determined as:

$$Q_t = \hat{Q}_t - (C_t - U_t) \quad (2.6)$$

The quantity of goods produced for consumption is determined by firms expectations for desired consumption. The extrapolative expectation rule is used by firms that believe consumption levels will continue shifting away from the long-run average quantity. This behavior is interpreted mathematically as:

$$U_t^E = C_{t-1} + c(C_{t-1} - \bar{C}) \quad (2.7)$$

where $c \geq 0$ denotes the speed at which firms expect consumption to deviate from the long-run level.

The other possible strategy firms can take is to expect consumption to return to the equilibrium level. This is described as the regressive expectation rule and is interpreted mathematically as:

$$U_t^R = C_{t-1} + f(\bar{C} - C_{t-1}) \quad (2.8)$$

where $0 \leq f \leq 1$ denotes the expected adjustment speed to the long-run level.

As this economy only involves two expectation rules, the aggregate expected level of consumption is a simple weighted average:

$$U_t = w_t U_t^E + (1 - w_t) U_t^R \quad (2.9)$$

The weight is defined as a function of consumption level which allows firms to switch their predictive behavior based on the current consumption level. Intuitively, as consumption deviates further from equilibrium, more firms will believe that the boom or slump will end and adjust in accordance. Likewise, when consumption is close to equilibrium, firms will believe it to be more accurate to extrapolate consumption. Weight is determined by the function:

$$w_t = \frac{1}{1 + d(\bar{C} - C_{t-1})^2} \quad (2.10)$$

where d is determined by the popularity of the regressive rule.

Taking these rules in aggregate, income is a second-order nonlinear iterated mapping. Condensing the model, we arrive at the mapping:

$$Y_t = U_t + kU_t - (1 + k)U_{t-1} + C_{t-1} + \bar{I} \quad (2.11)$$

This gives a single fixed point of:

$$\bar{Y} = \frac{1}{1 - b} \bar{I} \quad (2.12)$$

It is apparent that, as \bar{Y} is constant, the theoretical set-up of the model is only valid

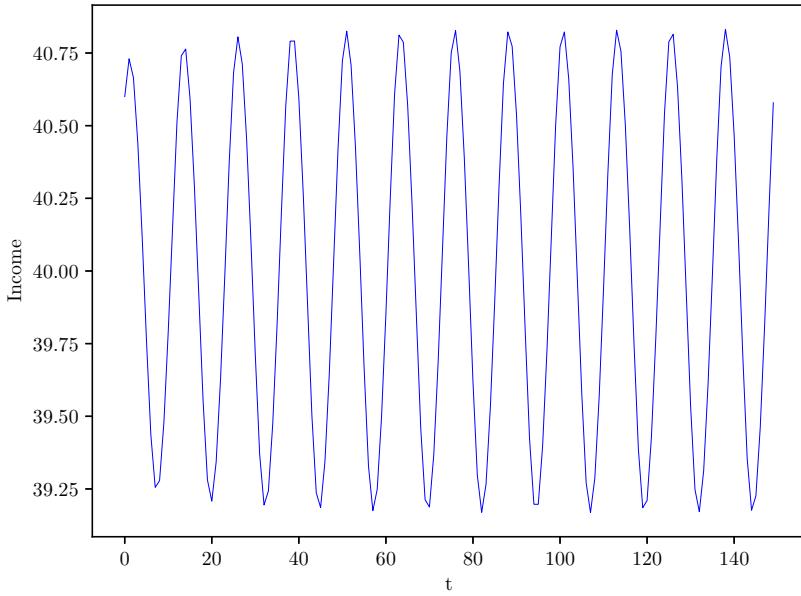


Figure 2.1: Timeseries plot of inventory cycle as described by Westerhoff et al.¹⁶ Simulation is determined given $Y_0 = 40.6$, $U_0 = 30.3$, and $\bar{I} = 10$. The parameters of the model are: $b = 0.75$, $c = 0.3$, $d = 1.0$, $f = 0.1$, $k = 0.1$. Income does not feature long-run growth but rather oscillates around the steady state level of income.

if there is no long-term growth. This is because the predictive mechanism used by firms is reliant on the difference between the lag in consumption and the steady-state level of consumption. If consumption were to consistently grow, then this difference would also grow over time, eliminating any effective purpose in providing heterogeneous expectations as firms would practically unanimously switch to the extrapolative mechanism.

2.3 Analysis of Income Dynamics

In the example trajectory given above, income clearly followed bounded, cyclic behavior. As seen with the analysis of the logistic map however, there are other types of long-term behavior possible. Given the restrictions on parameters, the steady-state level of income is stable if:

$$k < \frac{1 - b - bc}{b(1 + c)} \quad (2.13)$$

The proof for this can be seen in the appendix of Westerhoff et al.¹⁶ The stability of the steady state is only dependent on b , k , and c , thus the behavior of the regressive expectation rule and the ratio of firms behaving with each expectation rule do not affect

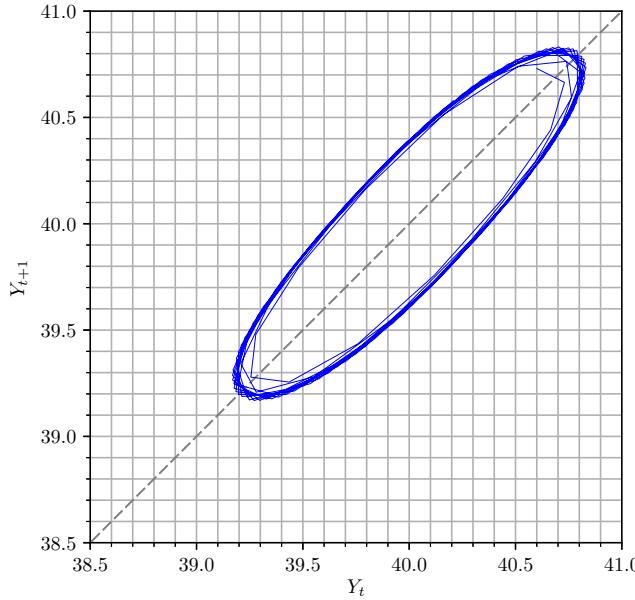


Figure 2.2: Cobweb plot of same trajectory in Figure 2.1. The beginning of the trajectory occurs at the point $(40.6, 40.6)$.

the stability of this fixed point. This can be seen graphically using bifurcation diagrams of the parameters.

There is a Neimark-Sacker bifurcation where $b \approx 0.65$ which marks a transition point from a stable fixed point to a bounded cycle. However, as b approaches 1, the bifurcation diagram does not graphically feature cycles of well defined order. Varying c and k alters the behavior of the cycles as seen in Figure 2.4 and 2.5. Altering d or f affects the magnitude of the inventory cycles but does not have any effect on the presence of the cycles.

The bifurcation diagrams varying the c , k , d , and f parameters appear to display clear cyclic behavior. However, this is actually a product of the graphical display of the bifurcation diagram. The diagram is constructed by iterating the mapping over 1000 time periods and displaying the results of the last 50 time-periods. This results in the appearance of 50-cycles over the span of the bifurcation diagram; however, reducing or increasing the amount of iterations to display likewise changes the apparent periodicity of the cycle.

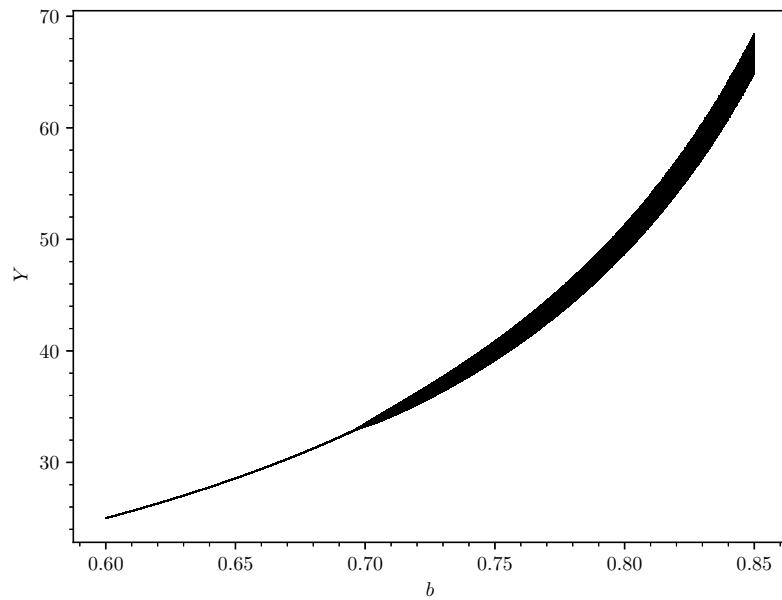


Figure 2.3: Bifurcations diagram varying the parameter b over the range $[0.2, 0.85]$ holding all other parameters and initial conditions as described in Figure 2.1. The simulation was allowed to run for 1000 iterations and the last 50 points are captured in the diagram.

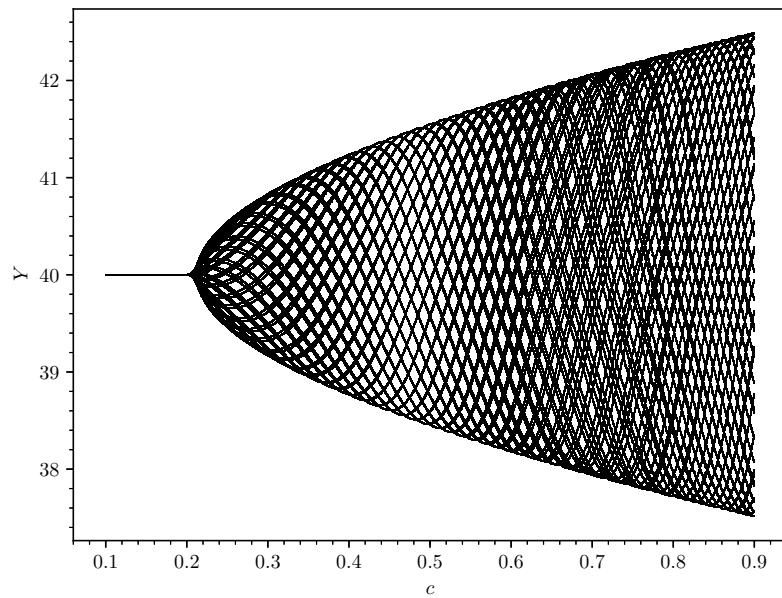


Figure 2.4: Bifurcations diagram varying the parameter c over the range $[0.1, 0.9]$ holding all other parameters and initial conditions as described in Figure 2.1. The simulation was allowed to run for 1000 iterations and the last 50 points are captured in the diagram.

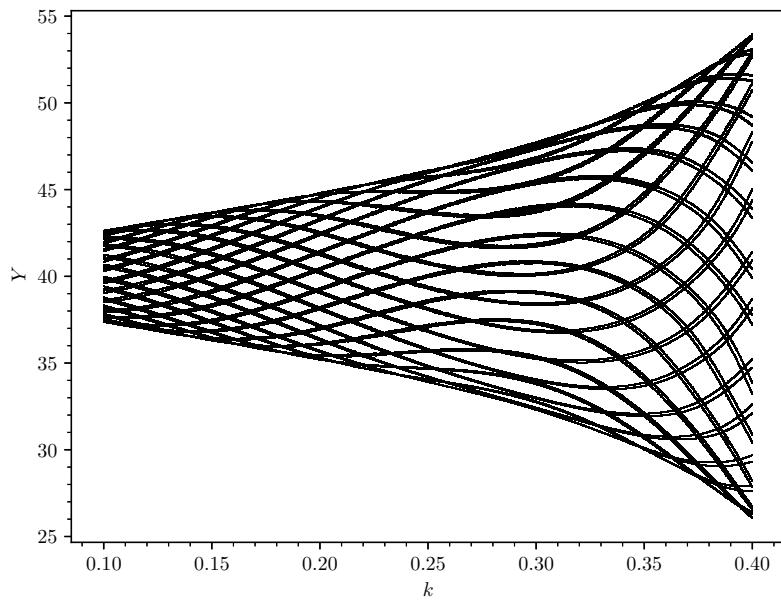


Figure 2.5: Bifurcations diagram varying the parameter k over the range $[0.1, 0.4]$ holding all other parameters and initial conditions as described in Figure 2.1. The simulation was allowed to run for 1000 iterations and the last 50 points are captured in the diagram.

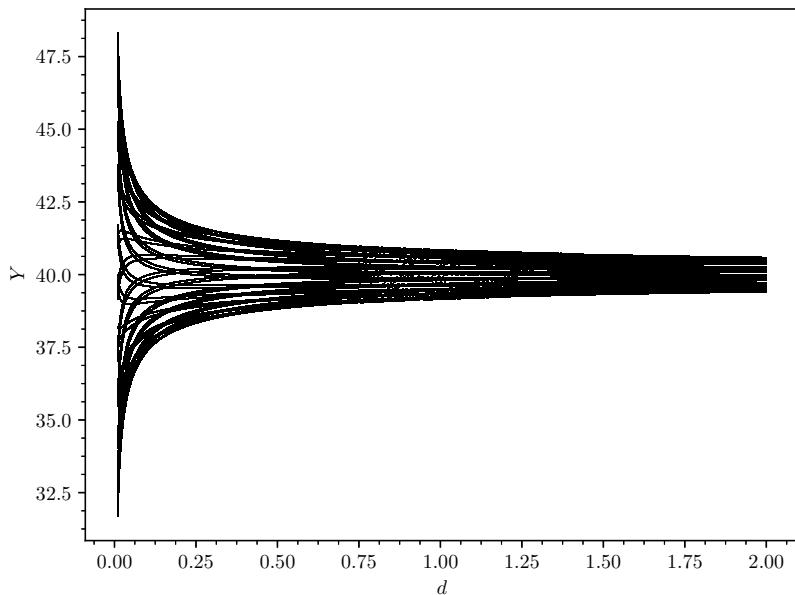


Figure 2.6: Bifurcations diagram varying the parameter d over the range $[0.01, 2.0]$ holding all other parameters and initial conditions as described in Figure 2.1. The simulation was allowed to run for 1000 iterations and the last 50 points are captured in the diagram.

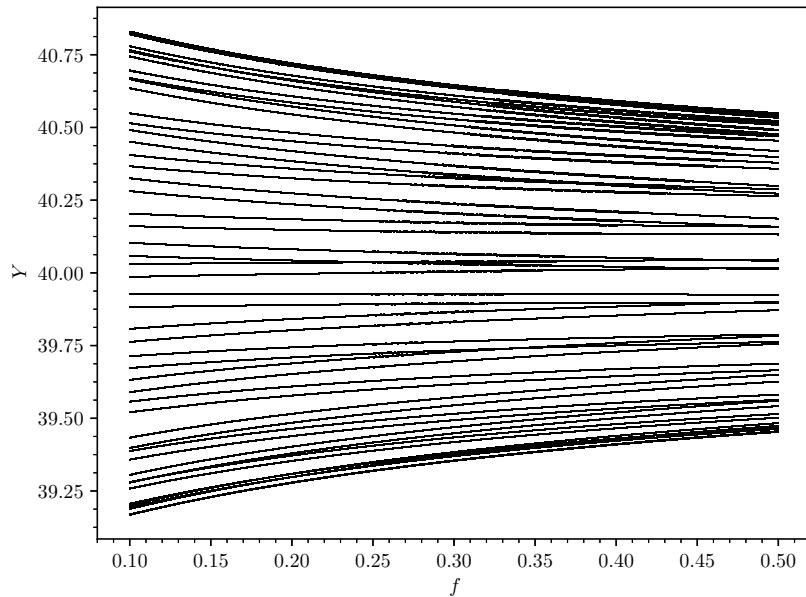


Figure 2.7: Bifurcations diagram varying the parameter f over the range $[0.1, 0.5]$ holding all other parameters and initial conditions as described in Figure 2.1. The simulation was allowed to run for 1000 iterations and the last 50 points are captured in the diagram.

3. Inventory Cycles with Averaged Expectations, Endogenous Investment, and Consumption Lag

3.1 Background

Metzler's and Westerhoff's model show that it is possible for endogenous business cycles to be induced through inventory cycles and the failure of firms to accurately predict future consumption. These models were designed to focus on the effects of firm expectations with Westerhoff's contribution consisting of introducing a heterogenous expectation rule that allows firms to switch behavior based on the state of the economy. Both of these models however simplify other aspects of the economy that feature more complex behavior in other business cycle models.

The inventory cycle model features 3 main factors of production: predicted consumption, investment, and inventory. Metzler and Westerhoff holds investment as an exogenously determined constant; however, this is both unrealistic and does not allow for long term endogenous growth. To incorporate a mechanism for endogenously adjusting investment, we take inspiration from the discrete time business cycle model described by Tönu Puu.¹² In order for investment to operate under Keynes' accelerator principle, capital stock must be in a proportion to the change in income, thus the investment level would be a function of the rate of change in income.

A linear function for investment captures this premise; however, this leads to unrealistic behavior for higher magnitudes of income change. Suppose income dramatically increased; a linear function implies that a proportionally high level of investment can sustain this higher level of production when in reality other factors of production such as the land, labor, or technology available are the primary limiting factors. Of larger concern with a linear model though is if the economy encounters a sharp decrease in income. This induces a large, negative value for investment which implies that firms would actively destroy their machinery and other forms of capital stock in the event of an economic recession. This is obviously unrealistic and so John Hicks introduced a piecewise linear investment function such that at extreme levels of income change, investment will reach a

predetermined maximal or minimal value. This piecewise function was then adapted to be differentiable over all points by Richard Goodwin by approximating the curve with a hyperbolic-tangent function.¹²

Puu approximates the hyperbolic-tangent function with its linear-cubic Taylor series expansion as this introduces a back-bending behavior into the curve. This allows the investment curve to capture not only firm behavior in the private sector but also implicitly include government spending and taxation. This follows from the now common policy for governments to engage in contracyclic behavior, increasing the quantity and size of spending projects and decreasing taxes when income is decreasing. Likewise, when the economy is performing well, the government cuts back on spending projects intended to stimulate the economy while also increasing taxes in order to take advantage of the overheating economy.

The problem with the cubic function is that it leads to unbounded behavior in the extremes, much like the linear function. Puu resolves this by ensuring that income growth is bounded by $[-1, 1]$; this is not the case for our model however. We instead want a function that features similar curvature and behavior as the cubic function but flattens when income change is of significant magnitude. This can be accomplished with the following function:

$$I_t = \frac{\frac{Y_{t-1} - Y_{t-2}}{v}}{\left(\frac{Y_{t-1} - Y_{t-2}}{v}\right)^4 + q} \quad (3.1)$$

The behavior of this function qualitatively resembles that of the linear-cubic function described in by Puu when $v, q > 0$ and ; however, $\lim_{(Y_{t-1} - Y_{t-2}) \rightarrow \infty} I_t = 0$. This function is at its absolute maximum and minimum when:

$$Y_{t-1} - Y_{t-2} = \pm \frac{q^{1/4}v}{3^{1/4}}$$

Thus giving a maximal or minimal investment of:

$$I_t = \frac{3^{3/4}}{4q^{3/4}}$$

Intuitively, larger values of v make the function "wider", increasing the range over $Y_{t-1} - Y_{t-2}$ where I_t is not effectively 0. Smaller values of q increases the magnitude of the maximum and minimum of the function, effectively making it taller. v and q cannot be directly attributed to any direct economic phenomena; however, their effect on the function can be interpreted analogously to the properties of the linear-cubic function. The

”height” of the function determines the potential magnitude of investment and the ”width” determines the rate at which investment, both private and public, react to changes in income.

Metzler describes the existence of two important lags in the study of Keynesian models. The Robertson lag is characterized by making current consumption a function of past income, i.e. consumption behavior lags behind current income. The Lundberg lag however concerns a discrepancy between the income level and the production decision of firms¹⁷. These lags are named after the two economists D. H. Robertson and Erik Lundberg who developed models that contained only their eponymous lag type. Although both lags are likely to exist in reality, most models only incorporate one lag due to the increased complexity associated with it. Metzler and Westerhoff make use of a Lundberg lag by making income a function of the predicted level of consumption as opposed to actual consumption. Tönu Puu’s model makes use of a Robertson in order to induce endogenous business cycles. Metzler himself does not claim that the Lundberg sequence is any more realistic than the Robertson sequence. Whichever lag has a longer time-period can be treated as of being greater importance but Metzler actually proposes a variety of scenarios that present contradicting conclusions. Suppose that decided their behavior on a quarterly basis but consumers altered their spending behavior with every paycheck, then it is no longer unrealistic to treat the Robertson lag as being of 0 length, i.e. nonexistent. If consumers revise their spending behavior every 6 months to a year, then it would actually be more realistic to include a non-zero Robertson lag while minimizing the Lundberg lag.

For the purposes of this model, we will include a non-zero Lundberg and Robertson lag. The consumption function is treated exactly as presented in Puu:

$$C_t = (1 - s)Y_{t-1} + sY_{t-2} \quad (3.2)$$

This function incorporates a 1-period Lundberg lag where $s \in [0, 1]$ is the marginal propensity to save. This function also contains a 2-period delayed consumption due to the marginal propensity to save, thus all income made in some period t can be thought of as being eventually spent in the period $t + 1$ and $t + 2$. Although intuitive, this explanation is not wholly accurate as the Lundberg lag does not imply saving of income to spend in the next period but rather that spending behavior is influenced only on the information of lagged income level. The choice of s dictates the relative importance of lagged income, a higher marginal propensity to save reduces the impact of income made in the previous time period but increases the effective impact of the income made two time periods ago.

As the economy is also making use of a Robertson lag, income is not directly a

function of consumption as may be seen in other models. Rather, income is viewed from a production standpoint. This is achieved by explicitly defining a predicted level of consumption. Westerhoff and Metzler use an equation similar to the form:

$$U_t = C_{t-1} + \eta(C_{t-1} - C_{t-2})$$

However, this assumes that firms have no way to adapt their coefficient of expectation η .

A new predictive mechanism requires that firms have bounded rationality. If firms possessed perfect rationality, then they would be able to perfectly predict consumption levels as consumption is based on lagged income, thus if we wish to maintain our Robertson lag, firms must still have bounded rationality. Another mechanism that firms can use that maintains better "memory" is that of an average.

$$U_t = \frac{C_{t-1} + C_{t-2} + C_{t-3}}{3} \quad (3.3)$$

This formulation is an average of the consumption levels of the past 3 time periods. The choice of three time periods is relatively arbitrary and higher order difference equations of the same form can be used; however these higher order formulations can result in a less mathematically tractable model.

Inventory production proceeds as seen in Chapter 2 with firms producing S_t explicitly to maintain Inventory at optimal levels:

$$S_t = kU_t - Q_{t-1} \quad (3.4)$$

where Q_t is the level of inventory maintained at the end of time t and $k \in [0, 1]$. This can be solved for as the sum of the previous inventory level, production intended for inventory, and the difference between production intended for consumption and the actual consumption level:

$$Q_t = Q_{t-1} + S_t + (U_t - C_t) \quad (3.5)$$

Income level, or output, can thus be written as a sum of production:

$$Y_t = I_t + S_t + U_t \quad (3.6)$$

However, as income has the capability of sustained growth under this model, it is preferable to analyze the rate of change of income in this model. In Appendix A, we show that the growth rate of the economy can be interpreted as a single variable, 6th order difference

equation on \dot{Y} :

$$\begin{aligned} \dot{Y}_t = & \frac{\frac{\dot{Y}_{t-1}}{v}}{\left(\frac{\dot{Y}_{t-1}}{v}\right)^4 + q} - \frac{\frac{\dot{Y}_{t-2}}{v}}{\left(\frac{\dot{Y}_{t-2}}{v}\right)^4 + q} + \\ & (1+k) \frac{(1-s)(\dot{Y}_{t-2} + \dot{Y}_{t-3} + \dot{Y}_{t-4}) + s(\dot{Y}_{t-3} + \dot{Y}_{t-4} + \dot{Y}_{t-5})}{3} - \\ & \left[(k+1) \frac{(1-s)(\dot{Y}_{t-3} + \dot{Y}_{t-4} + \dot{Y}_{t-5}) + s(\dot{Y}_{t-4} + \dot{Y}_{t-5} + \dot{Y}_{t-6})}{3} \right. \\ & \left. - (1-s)\dot{Y}_{t-2} - s\dot{Y}_{t-3} \right] \end{aligned} \quad (3.7)$$

3.2 Growth Dynamics

The long run dynamics of the model are highly dependent on the choice of initial conditions. Simulation of the model require a choice of 6 initial values of income change in addition to the parameter choice. If the 6 initial values are equivalent, all future iterations of the mapping are equal to this choice and the model remains in a stable steady state. It is both more interesting and realistic then to consider cases where there is variation in initial income growth. Figure 3.1 displays a possible trajectory of income growth. Under the

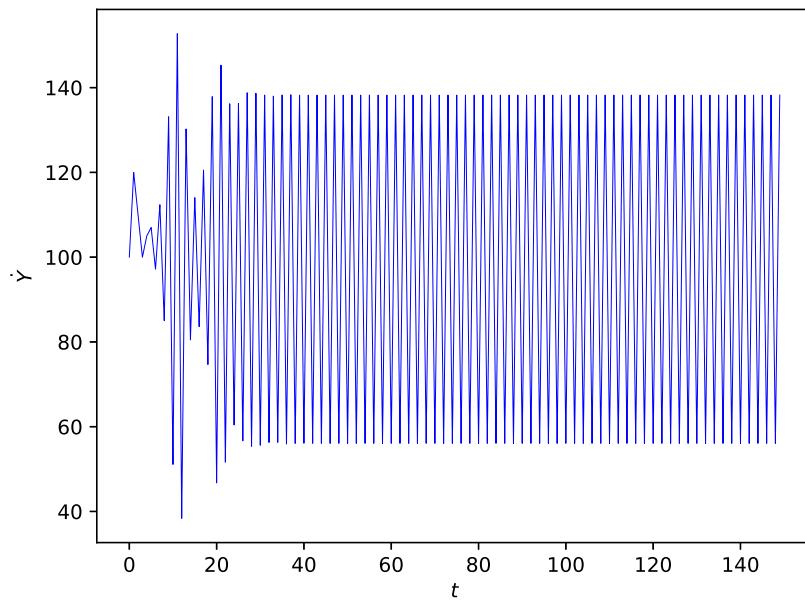


Figure 3.1: Timeseries plot of income growth rate over 150 iterations. $s = 0.6$, $k = 0.3$, $v = 500$, $q = 0.001$. Initial values of \dot{Y} are: 100, 120, 110, 100, 105, 107

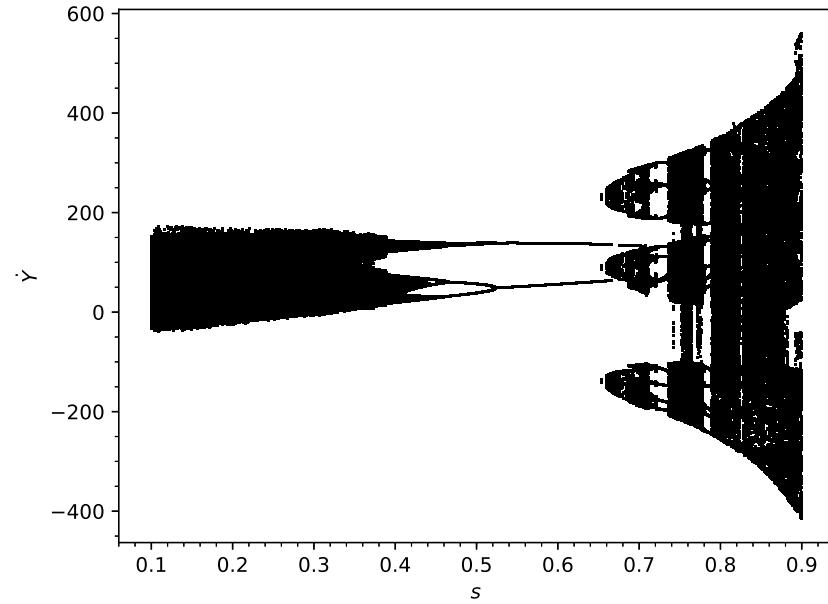


Figure 3.2: Bifurcation diagram varying s between 0.1 and 0.9. Initial conditions and other parameters are held constant as described in Figure 3.1.

parameters listed, the trajectory clearly behaves in a stable, cyclic manner within 40 iterations.

There do not exist techniques to solve generalized 6th order difference equations; however it is possible to computationally solve for the long run dynamics of the system.

The bifurcation diagram displayed in Figure 3.2 displays the long-run behavior of the model as s is varied. The methodology of the computational analysis and results are displayed in detail in Section D.4 and Section D.5, respectively. Long-run values are rounded to their nearest whole number for the purposes of this computational analysis although it is possible to account for higher levels of numerical precision using the analyzer. A bifurcation point exists at $s = 0.65$ and $s = 0.53$, the mapping is a stable 2 cycle when s is between these two values. This implies the presence of a stable business cycle when the marginal propensity to save is moderately high; however, the behavior appears chaotic when the marginal propensity to save approaches either extreme.

The bifurcation diagram varying k seen in Figure 3.3 qualitatively appears much simpler than Figure 3.2. This diagram displays a bifurcation point when $k \approx 0.84837$. The model displays stable 2-cycle behavior until this point although the system continues to display windows of ordered cycles. It thus appears that although increasing the desired proportional level of inventory does increase the long-run level of cyclic growth, it does

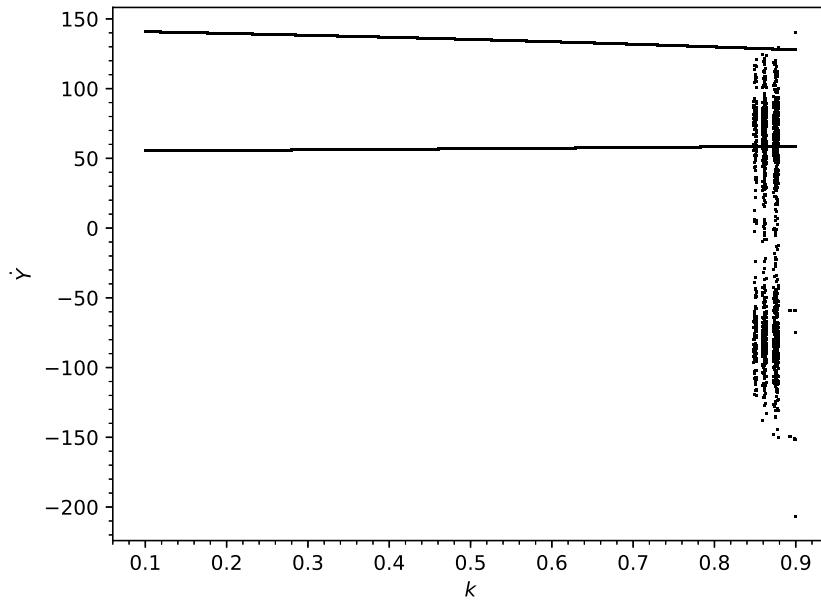


Figure 3.3: Bifurcation diagram varying k between 0.1 and 0.9. Initial conditions and other parameters are held constant as described in Figure 3.1.

not affect the topology until k is unrealistically large.

Figure 3.4 exhibits stable, fixed growth when $v \in [1, 297.338) \cup (617.104, 2000]$ which is the upper bound of what was computationally determined. The model also displays a stable 2-cycle when $v \in (472.173, 589.757)$. Likewise, Figure 3.5 has a bifurcation point at $q \approx 0.0015997$ and $q \approx 0.0015976$ which mark transitions from a stable, fixed point to a 2-period cycle to a 3-period cycle (more bifurcation points exist within the diagram and are more easily viewed by narrowing the parameter variation range). As stated previously, v and q individually lack an economic interpretation, but together they approximate the dynamics of a linear-cubic investment curve while incorporating bounded, asymptotic behavior.

These bifurcation diagrams do not tell the complete story of this model however for any given set of parameters. As stated previously,

3.2.1 Chaotic Behavior in Growth

Bifurcation analysis of this type allows us to determine the presence and location of bifurcation points separating arbitrary period cycles. However, this is insufficient to determine if varying the parameters of the model result in chaotic behavior and where exactly this transition occurs. The existence of chaos lends credence to the assumption of

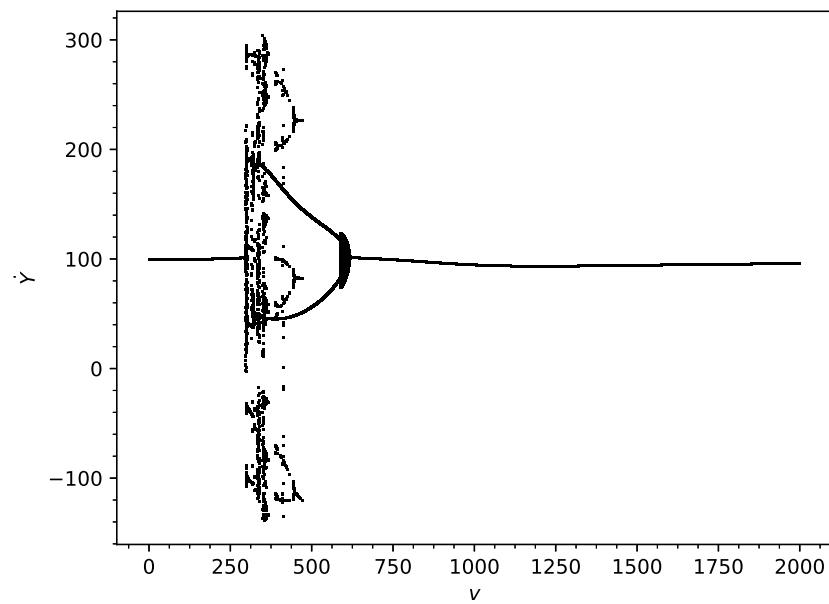


Figure 3.4: Bifurcation diagram varying v between 1 and 2000. Initial conditions and other parameters are held constant as described in Figure 3.1.

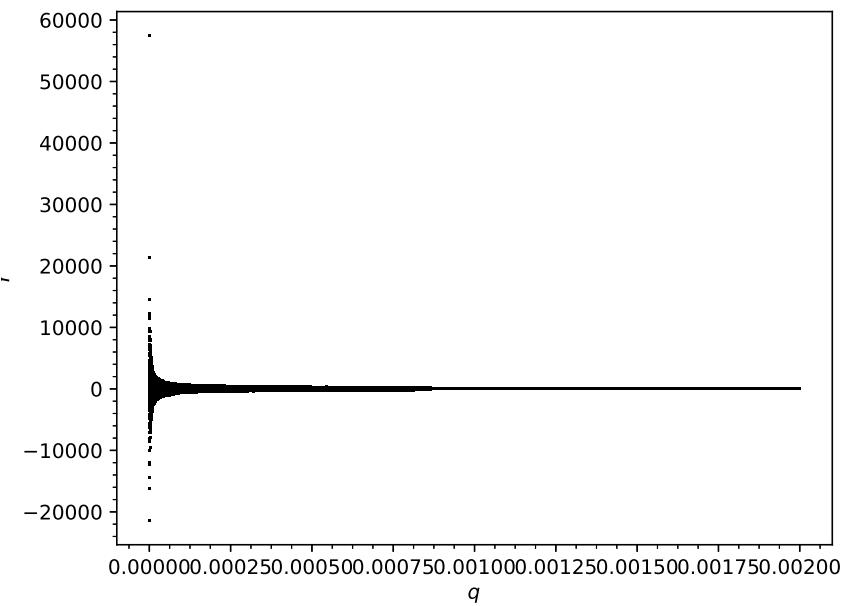


Figure 3.5: Bifurcation diagram varying q between 0 and 0.0001. Initial conditions and other parameters are held constant as described in Figure 3.1.

bounded rationality assigned to firms. If the model always features stable cycles, then it would only be logical that firms would eventually be able to adapt their predictive mechanism to predict this ordered behavior. The effect this shift in expectation rule would have on future dynamics is beyond the scope of this paper; however, the presence of chaos means the model is sufficiently sensitive to initial conditions that firms would not be able to accurately determine the future state of the market as under a chaotic system, knowing the approximate current state of the economy does not inform firms of the approximate future state of the economy.

We begin by rewriting the model as a 1st-order difference equation with 6 variables. This can be done by creating and defining the variables $\dot{Y}_{t-1} = \dot{A}_t$, $\dot{A}_{t-1} = \dot{B}_t$, $\dot{B}_{t-1} = \dot{C}_t$, $\dot{C}_{t-1} = \dot{D}_t$, and $\dot{D}_{t-1} = \dot{G}_t$. This allows us to define an equivalent model:

$$\begin{aligned}\dot{Y}_t &= f(\dot{Y}_{t-1}, \dot{A}_{t-1}, \dot{B}_{t-1}, \dot{C}_{t-1}, \dot{D}_{t-1}, \dot{G}_{t-1}) \\ \dot{A}_t &= g(\dot{Y}_{t-1}, \dot{A}_{t-1}, \dot{B}_{t-1}, \dot{C}_{t-1}, \dot{D}_{t-1}, \dot{G}_{t-1}) \\ \dot{B}_t &= h(\dot{Y}_{t-1}, \dot{A}_{t-1}, \dot{B}_{t-1}, \dot{C}_{t-1}, \dot{D}_{t-1}, \dot{G}_{t-1}) \\ \dot{C}_t &= j(\dot{Y}_{t-1}, \dot{A}_{t-1}, \dot{B}_{t-1}, \dot{C}_{t-1}, \dot{D}_{t-1}, \dot{G}_{t-1}) \\ \dot{D}_t &= l(\dot{Y}_{t-1}, \dot{A}_{t-1}, \dot{B}_{t-1}, \dot{C}_{t-1}, \dot{D}_{t-1}, \dot{G}_{t-1}) \\ \dot{G}_t &= m(\dot{Y}_{t-1}, \dot{A}_{t-1}, \dot{B}_{t-1}, \dot{C}_{t-1}, \dot{D}_{t-1}, \dot{G}_{t-1})\end{aligned}$$

The Jacobian matrix of this system of equations is:

$$J = \begin{bmatrix} \frac{\partial f}{\partial \dot{Y}_{t-1}} & \frac{\partial f}{\partial \dot{A}_{t-1}} & \frac{\partial f}{\partial \dot{B}_{t-1}} & \frac{\partial f}{\partial \dot{C}_{t-1}} & \frac{\partial f}{\partial \dot{D}_{t-1}} & \frac{\partial f}{\partial \dot{G}_{t-1}} \\ \frac{\partial g}{\partial \dot{Y}_{t-1}} & \frac{\partial g}{\partial \dot{A}_{t-1}} & \frac{\partial g}{\partial \dot{B}_{t-1}} & \frac{\partial g}{\partial \dot{C}_{t-1}} & \frac{\partial g}{\partial \dot{D}_{t-1}} & \frac{\partial g}{\partial \dot{G}_{t-1}} \\ \frac{\partial h}{\partial \dot{Y}_{t-1}} & \frac{\partial h}{\partial \dot{A}_{t-1}} & \frac{\partial h}{\partial \dot{B}_{t-1}} & \frac{\partial h}{\partial \dot{C}_{t-1}} & \frac{\partial h}{\partial \dot{D}_{t-1}} & \frac{\partial h}{\partial \dot{G}_{t-1}} \\ \frac{\partial j}{\partial \dot{Y}_{t-1}} & \frac{\partial j}{\partial \dot{A}_{t-1}} & \frac{\partial j}{\partial \dot{B}_{t-1}} & \frac{\partial j}{\partial \dot{C}_{t-1}} & \frac{\partial j}{\partial \dot{D}_{t-1}} & \frac{\partial j}{\partial \dot{G}_{t-1}} \\ \frac{\partial l}{\partial \dot{Y}_{t-1}} & \frac{\partial l}{\partial \dot{A}_{t-1}} & \frac{\partial l}{\partial \dot{B}_{t-1}} & \frac{\partial l}{\partial \dot{C}_{t-1}} & \frac{\partial l}{\partial \dot{D}_{t-1}} & \frac{\partial l}{\partial \dot{G}_{t-1}} \\ \frac{\partial m}{\partial \dot{Y}_{t-1}} & \frac{\partial m}{\partial \dot{A}_{t-1}} & \frac{\partial m}{\partial \dot{B}_{t-1}} & \frac{\partial m}{\partial \dot{C}_{t-1}} & \frac{\partial m}{\partial \dot{D}_{t-1}} & \frac{\partial m}{\partial \dot{G}_{t-1}} \end{bmatrix}$$

$$J = \begin{bmatrix} \frac{\partial f}{\partial \dot{Y}_{t-1}} & \frac{\partial f}{\partial \dot{A}_{t-1}} & s + \frac{k+1}{3}s & 0 & \frac{(k+1)(s-1)}{3} & -\frac{(k+1)s}{3} \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \quad (3.8)$$

where

$$\frac{\partial f}{\partial Y_{t-1}} = \frac{1}{v \left(q + \frac{Y_{t-1}^4}{v^4} \right)} - \frac{4Y_{t-1}^4}{v^5 \left(q + \frac{Y_{t-1}^4}{v^4} \right)}$$
$$\frac{\partial f}{\partial A_{t-1}} = 1 + \frac{1}{3}(k+1)(1-s) - s + \frac{4A_{t-1}^4}{v^5 \left(q + \frac{A_{t-1}^4}{v^4} \right)^2} - \frac{1}{v \left(q + \frac{A_{t-1}^4}{v^4} \right)}$$

4. Conclusion

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A. Solving for Change in Income

We can define the growth rate \dot{Y}_t as the difference in income between contiguous time periods:

$$\dot{Y}_t = Y_{t+1} - Y_t \quad (\text{A.1})$$

Let this dot notation refer to the analogous growth rate of other state variables. This equation can be expanded using Equation 3.6.

$$\dot{Y}_t = (U_{t+1} - U_t) + (I_{t+1} - I_t) + (S_{t+1} - S_t) = \dot{U}_t + \dot{I}_t + \dot{S}_t$$

The change in investment can be trivially solved for as investment is already a function of the change in income.

$$I_t = \frac{\frac{\dot{Y}_{t-2}}{v}}{\left(\frac{\dot{Y}_{t-2}}{v}\right)^4 + q}$$

Thus the change in investment is:

$$\dot{I}_t = \frac{\frac{\dot{Y}_{t-1}}{v}}{\left(\frac{\dot{Y}_{t-1}}{v}\right)^4 + q} - \frac{\frac{\dot{Y}_{t-2}}{v}}{\left(\frac{\dot{Y}_{t-2}}{v}\right)^4 + q} \quad (\text{A.2})$$

As predicted consumption is a function of the change in actual consumption, we must derive a function for the change in consumption in terms of the growth rate.

$$C_{t+1} - C_t = [(1-s)Y_t + sY_{t-1}] - [(1-s)Y_{t-1} + sY_{t-2}]$$

This can be simplified to:

$$\dot{C}_t = (1-s)(Y_t - Y_{t-1}) + s(Y_{t-1} - Y_{t-2}) = (1-s)\dot{Y}_{t-1} + s\dot{Y}_{t-2} \quad (\text{A.3})$$

The change in expected consumption can be given by:

$$U_{t+1} - U_t = \frac{C_t + C_{t-1} + C_{t-2}}{3} - \frac{C_{t-1} + C_{t-2} + C_{t-3}}{3}$$

$$\dot{U}_t = \frac{\dot{C}_{t-1} + \dot{C}_{t-2} + \dot{C}_{t-3}}{3}$$

This can be clearly resolved into a function of income growth rates:

$$\dot{U}_t = \frac{[(1-s)\dot{Y}_{t-2} + s\dot{Y}_{t-3}] + [(1-s)\dot{Y}_{t-3} + s\dot{Y}_{t-4}] + [(1-s)\dot{Y}_{t-4} + s\dot{Y}_{t-5}]}{3}$$

$$\dot{U}_t = \frac{1}{3} \left((1-s)(\dot{Y}_{t-2} + \dot{Y}_{t-3} + \dot{Y}_{t-4}) + s(\dot{Y}_{t-3} + \dot{Y}_{t-4} + \dot{Y}_{t-5}) \right) \quad (\text{A.4})$$

The final step is to solve for inventory production in terms of growth rates. We can substitute our S_t into our function for Q_t :

$$Q_t = Q_{t-1} + (kU_t - Q_{t-1} + (U_t - C_t))$$

$$Q_t = kU_t + U_t - C_t$$

This gives an equation for the rate of change:

$$Q_{t+1} - Q_t = [kU_{t+1} + U_{t+1} - C_{t+1}] - [kU_t + U_t - C_t]$$

$$\dot{Q}_t = (k+1)(U_{t+1}) - (k+1)(U_t) - (C_{t+1} - C_t)$$

$$\dot{Q}_t = (k+1)(U_{t+1} - U_t) - (C_{t+1} - C_t)$$

$$\dot{Q}_t = (k+1)(\dot{U}_t) - (\dot{C}_t)$$

Thus giving a function with respect to income growth rate:

$$\dot{Q}_t = \frac{k+1}{3} \left((1-s)(\dot{Y}_{t-2} + \dot{Y}_{t-3} + \dot{Y}_{t-4}) + s(\dot{Y}_{t-3} + \dot{Y}_{t-4} + \dot{Y}_{t-5}) \right) \quad (\text{A.5})$$

$$- (1-s)\dot{Y}_{t-1} - s\dot{Y}_{t-2}$$

The difference in production of goods for inventory is given by:

$$S_{t+1} - S_t = (kU_{t+1} - Q_t) - (kU_t - Q_{t-1})$$

$$\dot{S}_t = k(U_{t+1} - U_t) + Q_{t-1} - Q_t$$

$$\dot{S}_t = k(\dot{U}_t) - (\dot{Q}_{t-1})$$

We can thus substitute our functions for the change in predicted consumption and change

in inventory:

$$\begin{aligned}
 \dot{S}_t &= \frac{k}{3} \left((1-s)(\dot{Y}_{t-2} + \dot{Y}_{t-3} + \dot{Y}_{t-4}) + s(\dot{Y}_{t-3} + \dot{Y}_{t-4} + \dot{Y}_{t-5}) \right) - \\
 &\quad \left[\frac{k+1}{3} \left((1-s)(\dot{Y}_{t-3} + \dot{Y}_{t-4} + \dot{Y}_{t-5}) + s(\dot{Y}_{t-4} + \dot{Y}_{t-5} + \dot{Y}_{t-6}) \right) \right. \\
 &\quad \left. - (1-s)\dot{Y}_{t-2} - s\dot{Y}_{t-3} \right] \\
 \dot{S}_t &= \frac{k}{3} \left((1-s)(\dot{Y}_{t-2} + \dot{Y}_{t-3} + \dot{Y}_{t-4}) + s(\dot{Y}_{t-3} + \dot{Y}_{t-4} + \dot{Y}_{t-5}) \right) - \\
 &\quad \frac{k+1}{3} \left((1-s)(\dot{Y}_{t-3} + \dot{Y}_{t-4} + \dot{Y}_{t-5}) + s(\dot{Y}_{t-4} + \dot{Y}_{t-5} + \dot{Y}_{t-6}) \right) \\
 &\quad + (1-s)\dot{Y}_{t-2} + s\dot{Y}_{t-3}
 \end{aligned} \tag{A.6}$$

This means the function for the growth rate of the economy can be written as a 6th order, single-variable difference equation:

$$\begin{aligned}
 \dot{Y}_t &= \frac{\frac{\dot{Y}_{t-1}}{v}}{\left(\frac{\dot{Y}_{t-1}}{v}\right)^4 + q} - \frac{\frac{\dot{Y}_{t-2}}{v}}{\left(\frac{\dot{Y}_{t-2}}{v}\right)^4 + q} + \\
 &\quad \frac{1}{3} \left((1-s)(\dot{Y}_{t-2} + \dot{Y}_{t-3} + \dot{Y}_{t-4}) + s(\dot{Y}_{t-3} + \dot{Y}_{t-4} + \dot{Y}_{t-5}) \right) + \\
 &\quad \frac{k}{3} \left((1-s)(\dot{Y}_{t-2} + \dot{Y}_{t-3} + \dot{Y}_{t-4}) + s(\dot{Y}_{t-3} + \dot{Y}_{t-4} + \dot{Y}_{t-5}) \right) - \\
 &\quad \frac{k+1}{3} \left((1-s)(\dot{Y}_{t-3} + \dot{Y}_{t-4} + \dot{Y}_{t-5}) + s(\dot{Y}_{t-4} + \dot{Y}_{t-5} + \dot{Y}_{t-6}) \right) \\
 &\quad + (1-s)\dot{Y}_{t-2} + s\dot{Y}_{t-3} \\
 \dot{Y}_t &= \frac{\frac{\dot{Y}_{t-1}}{v}}{\left(\frac{\dot{Y}_{t-1}}{v}\right)^4 + q} - \frac{\frac{\dot{Y}_{t-2}}{v}}{\left(\frac{\dot{Y}_{t-2}}{v}\right)^4 + q} + \\
 &\quad \frac{k+1}{3} \left((1-s)(\dot{Y}_{t-2} + \dot{Y}_{t-3} + \dot{Y}_{t-4}) + s(\dot{Y}_{t-3} + \dot{Y}_{t-4} + \dot{Y}_{t-5}) \right) - \\
 &\quad \frac{k+1}{3} \left((1-s)(\dot{Y}_{t-3} + \dot{Y}_{t-4} + \dot{Y}_{t-5}) + s(\dot{Y}_{t-4} + \dot{Y}_{t-5} + \dot{Y}_{t-6}) \right) \\
 &\quad + (1-s)\dot{Y}_{t-2} + s\dot{Y}_{t-3} \\
 \dot{Y}_t &= \frac{\frac{\dot{Y}_{t-1}}{v}}{\left(\frac{\dot{Y}_{t-1}}{v}\right)^4 + q} - \frac{\frac{\dot{Y}_{t-2}}{v}}{\left(\frac{\dot{Y}_{t-2}}{v}\right)^4 + q} + \\
 &\quad \frac{k+1}{3} \left[(1-s)(\dot{Y}_{t-2} - Y_{t-5}) + s(\dot{Y}_{t-3} - Y_{t-6}) \right] + (1-s)\dot{Y}_{t-2} + s\dot{Y}_{t-3}
 \end{aligned} \tag{A.7}$$

B. Computational Analysis of the Logistic Map

B.1 Cobweb Plot

```
import numpy as np
from matplotlib import rc
import matplotlib.pyplot as plt

#LaTeX Font
rc('text', usetex=True)
rc('font', family='serif')

#Define Function
def logistic(u, x):
    return u * x * (1-x)

#Plots cobweb plot
def cobweb(u, X0, iterations):
    px, py = np.empty((2, iterations+1, 2))
    px[0], py[0] = X0, X0
    for i in range(1, iterations, 2):
        px[i] = px[i-1]
        py[i] = logistic(u, px[i-1])
        px[i+1] = py[i]
        py[i+1] = py[i]

    x = np.linspace(0,50,1000)
    fig = plt.figure(dpi=1000)
    ax = fig.add_subplot(111)
    ax.plot(x, x, c='gray', lw=1, dashes=[6,2])
    ax.plot(px, py, c='blue', linewidth=0.5)
```

```
#Beautify Plot
ax.minorticks_on()
ax.grid(which='minor', alpha=0.5)
ax.grid(which='major', alpha=0.5)
ax.axhline(0, color='k', lw=.5, alpha=0.25)
ax.axvline(0, color='k', lw=.5, alpha=0.25)
ax.set_aspect('equal')
ax.set_xlabel('$X_t$')
ax.set_ylabel('$X_{t+1}$')
ax.set_xlim(0, 1)
ax.set_ylim(0, 1)
cobweb(1.5, 0.1, 1000)
plt.savefig('./manuscript/figures/logistic/fixed_cob.eps', dpi=600)
cobweb(3.2, 0.799455, 1000)
plt.savefig('./manuscript/figures/logistic/2-cyclic_cob.eps', dpi=600)
cobweb(3.82842712, 0.5, 1000)
plt.savefig('./manuscript/figures/logistic/3-cyclic_cob.eps', dpi=600)
cobweb(3.8, 0.1, 1000)
plt.savefig('./manuscript/figures/logistic/chaos_cob.eps', dpi=600)
```

B.2 Bifurcation Diagram

```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import rc
import math
import statistics
#LaTeX Font
rc('text', usetex=True)
rc('font', family='serif')
```

```
def logistic(u, x):
    return u * x * (1-x)
#Define bifurcation plot
n = 1000
```

```
iterations = 1000
last = 100
x = 0.1 * np.ones(n)
u = np.linspace(0.0001, 4.0, n)
fig = plt.figure()
ax = fig.add_subplot(111)
for i in range(iterations):
    x = logistic(u, x)

    if i >=(iterations - last):
        ax.plot(u, x, ',k', alpha=0.25)

#Labelling
ax.minorticks_on()
ax.set_xlabel('$\mu$')
ax.set_ylabel('x')
ax.set_title('Bifurcation-Diagram')
#Save and show
plt.savefig('./manuscript/figures/logistic/bifurcation.eps', dpi=600)

plt.show()
```

B.3 Lyapunov Plot

```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import rc
import math
import statistics
from tqdm import tqdm
#LaTeX Font
rc('text', usetex=True)
rc('font', family='serif')

def logistic(r, x):
    return u * x * (1-x)
```

```
#Range of u values and interval between each
n = 10000
u = np.linspace(0.0001, 4.0, n)

#Higher iteration count increases approximation accuracy
iterations = 100000
#Set initial value
x0 = 0.1
x = 0.1 * np.ones(n)

#Lyapunov calculation
lyapunov = np.zeros(n)
fig = plt.figure()
ax = fig.add_subplot(111)

print('Solving for L')
for i in tqdm(range(iterations)):
    x = logistic(u, x)
    #Compute partial sums using log of absolute value of derivative
    lyapunov += np.log(np.abs(u * (1 - 2 * x)))

#Plotting Lyapunov
ax.plot(u[lyapunov < 0],
        lyapunov[lyapunov < 0] / iterations,
        'k', alpha=.5, ms=.5)
ax.plot(u[lyapunov >= 0],
        lyapunov[lyapunov >= 0] / iterations,
        'r', alpha=.5, ms=.5)

#Labelling
ax.minorticks_on()
ax.set_xlabel('$\mu$')
ax.set_ylabel('$\lambda$')
ax.set_title('Lyapunov Plot')
ax.set_ylim(-2, 1)
ax.axhline(0, color='k', lw=.5, alpha=.5)

#Save and show
```

```
plt.savefig('./manuscript/figures/logistic/lyapunov.eps', dpi=600)  
plt.show()
```

C. Computational Analysis of the Metzlerian Inventory Cycle Model with Heterogenous Expectation Rules

C.1 Timeseries Plot

```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import rc
import math
import statistics
from tqdm import tqdm
import scipy

#LaTeX Font
rc('text', usetex=True)
rc('font', family='serif')

#Define Function
def metzlerian(k, U, Ulag, Clag, Ibar):
    return U + k * U - (1 + k) * Ulag + Clag + Ibar
#Solves for steady state income
def ssincome(b, Ibar):
    return (1/(1-b)) * Ibar
#Solves for steady state consumption
def ssconsumption(b, Ybar):
    return b * Ybar
#Solves for U, goods produced for sale
def saledist(c, f, d, Cbar, Clag):
```

```

Uextrapolate = Clag + c * (Clag - Cbar)
Uregression = Clag + f * (Cbar - Clag)
w = 1 / (1 + d * (Cbar - Clag)**2)
return w * Uextrapolate + (1 - w)*Uregression
#Solves for consumption
def consumption(b, Ylag):
    return b * Ylag
#Solves for S, goods produced for stock
def stock(k, Ulag, Clag, U):
    Qhatlag = k * Ulag
    Qlag = Qhatlag - (Clag - Ulag)
    Qhat = k * U
    return Qhat - Qlag
#Plots timeseries data
def timeseries_plot(Income):
    fig = plt.figure(dpi=600)
    #Time series of mapping
    ax1 = fig.add_subplot(1, 1, 1)
    ax1.plot(Income, c='blue', linewidth=0.5)
    plt.ylabel('Income')
    plt.xlabel('t')
    plt.savefig('./manuscript/figures/metzlerian_basic/timeseries_income.eps', dpi=600)
    plt.show()
#Solves for timeseries data
def timeseries(b, c, d, f, k, Y0, U0, Ibar, iterations):
    Ybar = ssincome(b, Ibar)
    Cbar = ssconsumption(b, Ybar)
    Income = np.array([Y0]*iterations)
    Sale = np.array([U0]*iterations)
    Consumption = np.ones(iterations)
    for i in tqdm(range(1, iterations)):
        Consumption[i-1] = consumption(b, Income[i-1])
        Sale[i] = saledist(c, f, d, Cbar, Consumption[i-1])
        Income[i] = metzlerian(k, Sale[i], Sale[i-1], Consumption[i-1], Ibar)
    timeseries_plot(Income)

```

```
timeseries(0.75, 0.3, 1.0, 0.1, 0.1, 40.6, 30.3, 10, 150)
```

C.2 Cobweb Plot

```
import numpy as np
from matplotlib import rc
import matplotlib.pyplot as plt
from tqdm import tqdm

#LaTeX Font
rc('text', usetex=True)
rc('font', family='serif')

#define Function
def metzlerian(k, U, Ulag, Clag, Ibar):
    return U + k * U - (1 + k) * Ulag + Clag + Ibar
#Solves for steady state income
def ssincome(b, Ibar):
    return (1/(1-b)) * Ibar
#Solves for steady state consumption
def ssconsumption(b, Ybar):
    return b * Ybar
#Solves for U, goods produced for sale
def saledist(c, f, d, Cbar, Clag):
    Uextrapolate = Clag + c * (Clag - Cbar)
    Uregression = Clag + f * (Cbar - Clag)
    w = 1 / (1 + d * (Cbar - Clag)**2)
    return w * Uextrapolate + (1 - w) * Uregression
#Solves for consumption
def consumption(b, Ylag):
    return b * Ylag
#Solves for S, goods produced for stock
def stock(k, Ulag, Clag, U):
    qhatlag = k * Ulag
    Qlag = Qhatlag - (Clag - Ulag)
```

```
Qhat = k * U
#Plots cobweb plot
def cobweb(b, c, d, f, k, Y0, U0, Ibar, iterations):
    Ybar = ssincome(b, Ibar)
    Cbar = ssconsumption(b, Ybar)
    Income = np.array([Y0]*iterations)
    Sale = np.array([U0]*iterations)
    Consumption = np.ones(iterations)
    Stock = np.ones(iterations)
    for i in tqdm(range(1, iterations)):
        Consumption[i-1] = consumption(b, Income[i-1])
        Sale[i] = saledist(c, f, d, Cbar, Consumption[i-1])
        Income[i] = metzlerian(k, Sale[i], Sale[i-1], Consumption[i-1], Ibar)
    px = []
    py = []
    for i in range(iterations-1):
        px = np.append(px, Income[i])
        py = np.append(py, Income[i+1])
    print(px)
    print(py)

x = np.linspace(0,50,1000)
fig = plt.figure(dpi=1000)
ax = fig.add_subplot(111)
ax.plot(x, x, c='gray', lw=1, dashes=[6,2])
ax.plot(px, py, c='blue', linewidth=0.5)
#Beautify Plot
ax.minorticks_on()
ax.grid(which='minor', alpha=0.5)
ax.grid(which='major', alpha=0.5)
ax.axhline(0, color='k', lw=.5, alpha=0.25)
ax.axvline(0, color='k', lw=.5, alpha=0.25)
ax.set_aspect('equal')
ax.set_xlabel('$Y_t$')
ax.set_ylabel('$Y_{t+1}$')
ax.set_xlim(38.5, 41.0)
```

```
ax.set_ylim(38.5, 41.0)
plt.savefig('./manuscript/figures/metzlerian_basic/cobweb.eps')
plt.show()
cobweb(0.75, 0.3, 1.0, 0.1, 0.1, 40.6, 30.3, 10, 150)
```

C.3 Bifurcation Diagram

```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import rc
from tqdm import tqdm
import statistics

#LaTeX Font
rc('text', usetex=True)
rc('font', family='serif')

#define Function
def metzlerian(k, U, Ulag, Clag, Ibar):
    return U + k * U - (1 + k) * Ulag + Clag + Ibar
#Solves for steady state income
def ssincome(b, Ibar):
    return (1/(1-b)) * Ibar
#Solves for steady state consumption
def ssconsumption(b, Ybar):
    return b * Ybar
#Solves for U, goods produced for sale
def saledist(c, f, d, Cbar, Clag):
    Uextrapolate = Clag + c * (Clag - Cbar)
    Uregression = Clag + f * (Cbar - Clag)
    w = 1 / (1 + d * (Cbar - Clag)**2)
    return w * Uextrapolate + (1 - w)*Uregression
#Solves for consumption
def consumption(b, Ylag):
    return b * Ylag
#Solves for S, goods produced for stock
```

```

def stock(k, Ulag, Clag, U):
    Qhatlag = k * Ulag
    Qlag = Qhatlag - (Clag - Ulag)
    Qhat = k * U
    return Qhat - Qlag
#Solves for timeseries data
def timeseries(b, c, d, f, k, Y0, U0, Ibar, iterations):
    Ybar = ssincome(b, Ibar)
    Cbar = ssconsumption(b, Ybar)
    Income = np.array([Y0]*iterations)
    Sale = np.array([U0]*iterations)
    Consumption = np.ones(iterations)
    for i in range(1, iterations):
        Consumption[i-1] = consumption(b, Income[i-1])
        Sale[i] = saledist(c, f, d, Cbar, Consumption[i-1])
        Income[i] = metzlerian(k, Sale[i], Sale[i-1], Consumption[i-1], Ibar)
    return Income

#Bifurcation Diagram varying mpc, b
def bbifurcation(lower, upper, points, c, d, f, k, Y0, U0, Ibar):
    #Plot set up
    last = 50
    iterations = 1000
    fig = plt.figure(dpi=1000)
    ax = fig.add_subplot(111)
    #Generate distribution of parameter
    b = np.linspace(lower, upper, points)
    xaxis = np.repeat(b, last)
    yaxis = []
    #Solve for each parameter value
    print("b_Bifurcation")
    for j in tqdm(range(points)):
        Income = timeseries(b[j], c, d, f, k, Y0, U0, Ibar, iterations)
        lastvalues = Income[-last:]
        yaxis.extend(lastvalues)
    ax.plot(xaxis, yaxis, ',k', alpha=0.25)

```

```
#Labelling
ax.minorticks_on()
ax.set_xlabel('$b$')
ax.set_ylabel('$Y$')

#Save and show
plt.savefig('./manuscript/figures/metzlerian_basic/bbifurcation.eps', dpi=1500)

#Bifurcation Diagram varying expected deviation from equilibrium, c
def cbifurcation(lower, upper, points, b, d, f, k, Y0, U0, Ibar):
    #Plot set up
    last = 50
    iterations = 1000
    fig = plt.figure(dpi=1000)
    ax = fig.add_subplot(111)
    #Generate distribution of parameter
    c = np.linspace(lower, upper, points)
    xaxis = np.repeat(c, last)
    yaxis = []
    #Solve for each parameter value
    print("c_Bifurcation")
    for j in tqdm(range(points)):
        Income = timeseries(b, c[j], d, f, k, Y0, U0, Ibar, iterations)
        lastvalues = Income[-last:]
        yaxis.extend(lastvalues)
    ax.plot(xaxis, yaxis, 'k', alpha=0.25)
    #Labelling
    ax.minorticks_on()
    ax.set_xlabel('$c$')
    ax.set_ylabel('$Y$')

    #Save and show
    plt.savefig('./manuscript/figures/metzlerian_basic/cbifurcation.eps', dpi=1500)

#Bifurcation Diagram varying desired level of consumption relative to expected sale of
#consumption goods, k
def kbifurcation(lower, upper, points, b, c, d, f, Y0, U0, Ibar):
    #Plot set up
```

```
last = 50
iterations = 1000
fig = plt.figure(dpi=1000)
ax = fig.add_subplot(111)
#Generate distribution of parameter
k = np.linspace(lower, upper, points)
xaxis = np.repeat(k, last)
yaxis = []
#Solve for each parameter value
print("k_Bifurcation")
for j in tqdm(range(points)):
    Income = timeseries(b, c, d, f, k[j], Y0, U0, Ibar, iterations)
    lastvalues = Income[-last:]
    yaxis.extend(lastvalues)
    ax.plot(xaxis, yaxis, ',k', alpha=0.25)
#Labelling
ax.minorticks_on()
ax.set_xlabel('$k$')
ax.set_ylabel('$Y$')

#Save and show
plt.savefig('./manuscript/figures/metzlerian_basic/kbifurcation.eps', dpi=1500)

#Bifurcation Diagram varying popularity of regressive expectations, d
def dbifurcation(lower, upper, points, b, c, f, k, Y0, U0, Ibar):
    #Plot set up
    last = 50
    iterations = 1000
    fig = plt.figure(dpi=1000)
    ax = fig.add_subplot(111)
    #Generate distribution of parameter
    d = np.linspace(lower, upper, points)
    xaxis = np.repeat(d, last)
    yaxis = []
    #Solve for each parameter value
    print("d_Bifurcation")
```

```
for j in tqdm(range(points)):  
    Income = timeseries(b, c, d[j], f, k, Y0, U0, Ibar, iterations)  
    lastvalues = Income[-last:]  
    yaxis.extend(lastvalues)  
    ax.plot(xaxis, yaxis, ',k', alpha=0.25)  
    #Labelling  
    ax.minorticks_on()  
    ax.set_xlabel('$d$')  
    ax.set_ylabel('$Y$')  
  
    #Save and show  
    plt.savefig('./manuscript/figures/metzlerian_basic/dbifurcation.eps', dpi=1500)  
  
#Improved efficiency bifurcation diagram varying f  
def fbifurcation(lower, upper, points, b, c, d, k, Y0, U0, Ibar):  
    #Plot set up  
    last = 50  
    iterations = 1000  
    fig = plt.figure(dpi=1000)  
    ax = fig.add_subplot(111)  
    #Generate distribution of parameter  
    f = np.linspace(lower, upper, points)  
    xaxis = np.repeat(f, last)  
    yaxis = []  
    #Solve for each parameter value  
    print("f_Bifurcation")  
    for j in tqdm(range(points)):  
        Income = timeseries(b, c, d, f[j], k, Y0, U0, Ibar, iterations)  
        lastvalues = Income[-last:]  
        yaxis.extend(lastvalues)  
        ax.plot(xaxis, yaxis, ',k', alpha=0.25)  
        #Labelling  
        ax.minorticks_on()  
        ax.set_xlabel('$f$')  
        ax.set_ylabel('$Y$')
```

```
#Save and show
plt.savefig('./manuscript/figures/metzlerian_basic/fbifurcation.eps', dpi=1500)

bbifurcation(0.6, 0.85, 10000, 0.3, 1.0, 0.1, 0.1, 40.6, 30.5, 10)
cbifurcation(0.1, 0.9, 10000, 0.75, 1.0, 0.1, 0.1, 40.5, 30.5, 10)
kbifurcation(0.1, 0.4, 10000, 0.75, 0.3, 0.1, 0.1, 40.5, 30.5, 10)
dbifurcation(0.01, 2.0, 10000, 0.75, 0.3, 0.1, 0.1, 40.5, 30.5, 10)
fbifurcation(0.1, 0.5, 10000, 0.75, 0.3, 1.0, 0.1, 40.0, 30.5, 10)
```

D. Computational Analysis of the Metzlerian Inventory Cycle Model with Averaged Expectations, Endogenous Investment, and Consumption Lag

D.1 Timeseries Plot

```
import numpy as np
import matplotlib.pyplot as plt
from tqdm import tqdm
#Time series with mean of last 3 prediction
def growth(dYt1, dYt2, dYt3, dYt5, dYt6, s, k, v, q):
    dYt = (dYt1 / v) / ((dYt1 / v)**4 + q) - (dYt2 / v) / ((dYt2 / v)**4 + q) +
        ((k+1)/3) * ((1-s)*(dYt2-dYt5)+s*(dYt3-dYt6)) + (1-s)*dYt2 + s*dYt3
    return dYt

#Plot timeseries
def variableplot(Variable):
    fig = plt.figure(dpi=600)
    #Time series of mapping
    ax1 = fig.add_subplot(1, 1, 1)
    ax1.plot(Variable, c='blue', linewidth=0.5)
    ax1.set_xlabel('$t$')
    ax1.set_ylabel('$\dot{Y}$')

def mapping(dY0, dY1, dY2, dY3, dY4, dY5, s, k, v, q, iter):
    #Initialize vectors
    dY = np.append([dY0, dY1, dY2, dY3, dY4, dY5], np.zeros(iter-6))
    #Simulate
```

```
for t in tqdm(range(6, iter)):
    dY[t] = growth(dY[t-1], dY[t-2], dY[t-3], dY[t-5], dY[t-6], s, k, v, q)
variableplot(dY)
return dY

mapping(100, 120, 110, 100, 105, 107, 0.6, 0.3, 500, 0.001, 150)
plt.savefig('./manuscript/figures/metzlerian_growth/timeseries1.eps', dpi=1200)
mapping(100, 120, 110, 100, 105, 107, 0.7, 0.3, 500, 0.001, 200)
plt.savefig('./manuscript/figures/metzlerian_growth/timeseries2.eps', dpi=1200)
mapping(29, 20 , 15 , 10, 20 ,50, 0.6, 0.3, 500, 0.001, 150)
plt.savefig('./manuscript/figures/metzlerian_growth/timeseries3.eps', dpi=1200)
```

D.2 Bifurcation Diagram Varying Parameters

```
import numpy as np
import matplotlib.pyplot as plt
from tqdm import tqdm

#Time series with mean of last 3 prediction
#Time series with mean of last 3 prediction
def growth(dYt1, dYt2, dYt3, dYt5, dYt6, s, k, v, q):
    dYt = (dYt1 / v) / ((dYt1 / v)**4 + q) - (dYt2 / v) / ((dYt2 / v)**4 + q) +
        ((k+1)/3) * ((1-s)*(dYt2-dYt5)+s*(dYt3-dYt6)) + (1-s)*dYt2 + s*dYt3
    return dY

def mapping(dY0, dY1, dY2, dY3, dY4, dY5, s, k, v, q, iter):
    #Initialize vectors
    dY = np.append([dY0, dY1, dY2, dY3, dY4, dY5], np.zeros(iter-6))
    #Simulate
    for t in range(6, iter):
        dY[t] = growth(dY[t-1], dY[t-2], dY[t-3], dY[t-5], dY[t-6], s, k, v, q)
    return dY

def sbifurcation(lower, upper, points, dY0, dY1, dY2, dY3, dY4, dY5, k, v, q):
    #Plot set up
```

```
last = 30
iterations = 2000
fig = plt.figure(dpi=1200)
ax = fig.add_subplot(111)
#Generate distribution of parameter
s = np.linspace(lower, upper, points)
xaxis = np.repeat(s, last)
yaxis = []
#Solve for each parameter value
print("s_Bifurcation")
for j in tqdm(range(points)):
    Income = mapping(dY0, dY1, dY2, dY3, dY4, dY5, s[j], k, v, q, iterations)
    for m in range(iterations):
        if m >= (iterations - last):
            yaxis = np.append(yaxis, Income[m])
    ax.plot(xaxis, yaxis, ',k', alpha=0.25)
#Labelling
ax.minorticks_on()
ax.set_xlabel('$$')
ax.set_ylabel('$\dot{Y}$')
#Save and show

def kbifurcation(lower, upper, points, dY0, dY1, dY2, dY3, dY4, dY5, s, v, q):
    #Plot set up
    last = 20
    iterations = 1000
    fig = plt.figure(dpi=1200)
    ax = fig.add_subplot(111)
    #Generate distribution of parameter
    k = np.linspace(lower, upper, points)
    xaxis = np.repeat(k, last)
    yaxis = []
    #Solve for each parameter value
    print("k_Bifurcation")
    for j in tqdm(range(points)):
        Income = mapping(dY0, dY1, dY2, dY3, dY4, dY5, s, k[j], v, q, iterations)
```

```
for m in range(iterations):
    if m >= (iterations - last):
        yaxis = np.append(yaxis, Income[m])
    ax.plot(xaxis, yaxis, ',k', alpha=0.25)
    #Labelling
    ax.minorticks_on()
    ax.set_xlabel('$k$')
    ax.set_ylabel('$\dot{Y}$')
    #Save and show

def qbifurcation(lower, upper, points, dY0, dY1, dY2, dY3, dY4, dY5, s, k, v):
    #Plot set up
    last = 20
    iterations = 1000
    fig = plt.figure(dpi=1200)
    ax = fig.add_subplot(111)
    #Generate distribution of parameter
    q = np.linspace(lower, upper, points)
    xaxis = np.repeat(q, last)
    yaxis = []
    #Solve for each parameter value
    print("q-Bifurcation")
    for j in tqdm(range(points)):
        Income = mapping(dY0, dY1, dY2, dY3, dY4, dY5, s, k, v, q[j], iterations)
        for m in range(iterations):
            if m >= (iterations - last):
                yaxis = np.append(yaxis, Income[m])
            ax.plot(xaxis, yaxis, ',k', alpha=0.25)
            #Labelling
            ax.minorticks_on()
            ax.set_xlabel('$q$')
            ax.set_ylabel('$\dot{Y}$')
            #Save and show

def vbifurcation(lower, upper, points, dY0, dY1, dY2, dY3, dY4, dY5, s, k, q):
```

```
#Plot set up
last = 20
iterations = 1000
fig = plt.figure(dpi=1200)
ax = fig.add_subplot(111)
#Generate distribution of parameter
v = np.linspace(lower, upper, points)
xaxis = np.repeat(v, last)
yaxis = []
#print("v_Bifurcation")
for j in tqdm(range(points)):
    Income = mapping(dY0, dY1, dY2, dY3, dY4, dY5, s, k, v[j], q, iterations)
    for m in range(iterations):
        if m >= (iterations - last):
            yaxis = np.append(yaxis, Income[m])
    ax.plot(xaxis, yaxis, ',k', alpha=0.25)
#Labelling
ax.minorticks_on()
ax.set_xlabel('$v$')
ax.set_ylabel('$\dot{Y}$')

sbifurcation(0.1, 0.9, 10000, 100, 120, 110, 100, 105, 107, 0.3, 500, 0.001)
plt.savefig('./manuscript/figures/metzlerian_growth/sbifurcation.eps', dpi=1200)
kbifurcation(0.1, 0.9, 10000, 100, 120, 110, 100, 105, 107, 0.6, 500, 0.001)
plt.savefig('./manuscript/figures/metzlerian_growth/kbifurcation.eps', dpi=1200)
kbifurcation(0.1, 0.9, 10000, 100, 120, 110, 100, 105, 107, 0.7, 500, 0.001)
plt.savefig('./manuscript/figures/metzlerian_growth/kbifurcation2.eps', dpi=1200)
vbifurcation(1, 2000, 10000, 100, 120, 110, 100, 105, 107, 0.6, 0.3, 0.001)
plt.savefig('./manuscript/figures/metzlerian_growth/vbifurcation.eps', dpi=1200)
qbifurcation(0, 0.002, 10000, 100, 120, 110, 100, 105, 107, 0.6, 0.3, 500)
plt.savefig('./manuscript/figures/metzlerian_growth/qbifurcation.eps', dpi=1200)
```

D.3 Bifurcation Diagram Varying Initial Conditions

```
import numpy as np
```

```
import matplotlib.pyplot as plt
from tqdm import tqdm

#Time series with mean of last 3 prediction
def growth(dYt1, dYt2, dYt3, dYt5, dYt6, s, k, v, q):
    dYt = (dYt1 / v) / ((dYt1 / v)**4 + q) - (dYt2 / v) / ((dYt2 / v)**4 + q) +
          ((k+1)/3) * ((1-s)*(dYt2-dYt5)+s*(dYt3-dYt6)) + (1-s)*dYt2 + s*dYt3
    return dY

#Creates mapping for growth model based on growth function
def mapping(dY0, dY1, dY2, dY3, dY4, dY5, s, k, v, q, iter):
    #Initialize vectors
    dY = np.append([dY0, dY1, dY2, dY3, dY4, dY5], np.zeros(iter-6))
    #Simulate
    for t in range(6, iter):
        dY[t] = growth(dY[t-1], dY[t-2], dY[t-3], dY[t-5], dY[t-6], s, k, v, q)
    return dY

def y0bifurcation(lower, upper, points, dY1, dY2, dY3, dY4, dY5, s, k, v, q):
    #Plot set up
    last = 20
    iterations = 1000
    fig = plt.figure(dpi=1200)
    ax = fig.add_subplot(111)
    #Generate distribution of parameter
    Y0 = np.linspace(lower, upper, points)
    xaxis = np.repeat(Y0, last)
    yaxis = []
    #Solve for each parameter value
    print("\dot{Y}_0 Bifurcation")
    for j in tqdm(range(points)):
        Income = mapping(Y0[j], dY1, dY2, dY3, dY4, dY5, s, k, v, q, iterations)
        lastvalues = Income[-last:]
        yaxis.extend(lastvalues)
    ax.plot(xaxis, yaxis, 'k', alpha=0.25)
    #Labelling
```

```
ax.minorticks_on()
ax.set_xlabel('$\dot{Y}_0$')
ax.set_ylabel('$\dot{Y}$')

def y1bifurcation(lower, upper, points, dY0, dY2, dY3, dY4, dY5, s, k, v, q):
    #Plot set up
    last = 20
    iterations = 1000
    fig = plt.figure(dpi=1200)
    ax = fig.add_subplot(111)
    #Generate distribution of parameter
    Y1 = np.linspace(lower, upper, points)
    xaxis = np.repeat(Y1, last)
    yaxis = []
    #Solve for each parameter value
    print("$\dot{Y}_1$-Bifurcation")
    for j in tqdm(range(points)):
        Income = mapping(dY0, Y1[j], dY2, dY3, dY4, dY5, s, k, v, q, iterations)
        lastvalues = Income[-last:]
        yaxis.extend(lastvalues)
    ax.plot(xaxis, yaxis, ',k', alpha=0.25)
    #Labelling
    ax.minorticks_on()
    ax.set_xlabel('$\dot{Y}_1$')
    ax.set_ylabel('$\dot{Y}$')

def y2bifurcation(lower, upper, points, dY0, dY1, dY3, dY4, dY5, s, k, v, q):
    #Plot set up
    last = 20
    iterations = 1000
    fig = plt.figure(dpi=1200)
    ax = fig.add_subplot(111)
    #Generate distribution of parameter
    Y2 = np.linspace(lower, upper, points)
    xaxis = np.repeat(Y2, last)
    yaxis = []
```

```
#Solve for each parameter value
print("\$dot_Y_2$ Bifurcation")
for j in tqdm(range(points)):
    Income = mapping(dY0, dY1, Y2[j], dY3, dY4, dY5, s, k, v, q, iterations)
    lastvalues = Income[-last:]
    yaxis.extend(lastvalues)
    ax.plot(xaxis, yaxis, ',k', alpha=0.25)
#Labelling
ax.minorticks_on()
ax.set_xlabel('$dot_Y_2$')
ax.set_ylabel('$dot_Y$')

def y3bifurcation(lower, upper, points, dY0, dY1, dY2, dY4, dY5, s, k, v, q):
    #Plot set up
    last = 20
    iterations = 1000
    fig = plt.figure(dpi=1200)
    ax = fig.add_subplot(111)
    #Generate distribution of parameter
    Y3 = np.linspace(lower, upper, points)
    xaxis = np.repeat(Y3, last)
    yaxis = []
    #Solve for each parameter value
    print("\$dot_Y_3$ Bifurcation")
    for j in tqdm(range(points)):
        Income = mapping(dY0, dY1, dY2, Y3[j], dY4, dY5, s, k, v, q, iterations)
        lastvalues = Income[-last:]
        yaxis.extend(lastvalues)
        ax.plot(xaxis, yaxis, ',k', alpha=0.25)
    #Labelling
    ax.minorticks_on()
    ax.set_xlabel('$dot_Y_3$')
    ax.set_ylabel('$dot_Y$')

def y4bifurcation(lower, upper, points, dY0, dY1, dY2, dY3, dY5, s, k, v, q):
    #Plot set up
```

```
last = 20
iterations = 1000
fig = plt.figure(dpi=1200)
ax = fig.add_subplot(111)
#Generate distribution of parameter
Y4 = np.linspace(lower, upper, points)
xaxis = np.repeat(Y4, last)
yaxis = []
#Solve for each parameter value
print("$\dot{Y}_4$-Bifurcation")
for j in tqdm(range(points)):
    Income = mapping(dY0, dY1, dY2, dY3, Y4[j], dY5, s, k, v, q, iterations)
    lastvalues = Income[-last:]
    yaxis.extend(lastvalues)
    ax.plot(xaxis, yaxis, 'k', alpha=0.25)
#Labelling
ax.minorticks_on()
ax.set_xlabel('$\dot{Y}_4$')
ax.set_ylabel('$\dot{Y}$')

def y5bifurcation(lower, upper, points, dY0, dY1, dY2, dY3, dY4, s, k, v, q):
    #Plot set up
    last = 20
    iterations = 1000
    fig = plt.figure(dpi=1200)
    ax = fig.add_subplot(111)
    #Generate distribution of parameter
    Y5 = np.linspace(lower, upper, points)
    xaxis = np.repeat(Y5, last)
    yaxis = []
    #Solve for each parameter value
    print("$\dot{Y}_5$-Bifurcation")
    for j in tqdm(range(points)):
        Income = mapping(dY0, dY1, dY2, dY3, dY4, Y5[j], s, k, v, q, iterations)
        lastvalues = Income[-last:]
        yaxis.extend(lastvalues)
```

```
ax.plot(xaxis, yaxis, 'k', alpha=0.25)
#Labelling
ax.minorticks_on()
ax.set_xlabel('$\dot{Y}_5$')
ax.set_ylabel('$\dot{Y}$')

y0bifurcation(-400, 400, 10000, 120, 110, 100, 105, 107, 0.6, 0.3, 500, 0.001)
plt.savefig('./manuscript/figures/metzlerian_growth/y0bifurcation.eps', dpi=1200)
y1bifurcation(-400, 400, 10000, 100, 110, 100, 105, 107, 0.6, 0.3, 500, 0.001)
plt.savefig('./manuscript/figures/metzlerian_growth/y1bifurcation.eps', dpi=1200)
y2bifurcation(-400, 400, 10000, 100, 120, 100, 105, 107, 0.6, 0.3, 500, 0.001)
plt.savefig('./manuscript/figures/metzlerian_growth/y2bifurcation.eps', dpi=1200)
y3bifurcation(-400, 400, 10000, 100, 120, 110, 105, 107, 0.6, 0.3, 500, 0.001,)
plt.savefig('./manuscript/figures/metzlerian_growth/y3bifurcation.eps', dpi=1200)
y4bifurcation(-400, 400, 10000, 100, 120, 110, 100, 107, 0.6, 0.3, 500, 0.001)
plt.savefig('./manuscript/figures/metzlerian_growth/y4bifurcation.eps', dpi=1200)
y5bifurcation(-400, 400, 10000, 100, 120, 110, 100, 105, 0.6, 0.3, 500, 0.001)
plt.savefig('./manuscript/figures/metzlerian_growth/y5bifurcation.eps', dpi=1200)
```

D.4 Bifurcation Analyzer

```
import numpy as np
import matplotlib.pyplot as plt
from tqdm import tqdm

#Create growth formula
#Time series with mean of last 3 prediction
def growth(dYt1, dYt2, dYt3, dYt5, dYt6, s, k, v, q):
    dYt = (dYt1 / v) / ((dYt1 / v)**4 + q) - (dYt2 / v) / ((dYt2 / v)**4 + q) +
        ((k+1)/3) * ((1-s)*(dYt2-dYt5)+s*(dYt3-dYt6)) + (1-s)*dYt2 + s*dYt3
    return dYt

#Creates mapping for growth model based on growth function
def mapping(dY0, dY1, dY2, dY3, dY4, dY5, s, k, v, q, iter):
    #Initialize vectors
    dY = np.append([dY0, dY1, dY2, dY3, dY4, dY5], np.zeros(iter-6))
```

```

#Simulate
for t in range(6, iter):
    dY[t] = growth(dY[t-1], dY[t-2], dY[t-3], dY[t-5], dY[t-6], s, k, v, q,)
return dY

def lbifurana(lower, upper, points, Yaxis, lsearch, period, precis):
    last = 30
    param = np.linspace(lower, upper, points)
    Xaxis = np.repeat(param, last)
    bifurfound = False
    i = np.nonzero(Xaxis >= lsearch)
    i = i[0][0]
    while bifurfound == False:
        ydat = [Yaxis[i]]
        for j in range(i+1, i+last):
            ydat = np.append(ydat, Yaxis[j])
        count = len(set(np.round(ydat, precis)))
        if count != period:
            print("Bifurcation_Point_Found_Searching")
            bifurfound = True
            print("Period_Shift_from")
            print(period)
            print("Bifurcation_Point_at")
            print(Xaxis[i])
            print("Points")
            print(set(np.round(ydat, precis)))
        else:
            i += last
    results.write(f'Bifurcation_Point_found_starting_search_from_{lsearch},_left_to_
        right_from_{period}_cycle.\n')
    results.write(f'Bifurcation_Point_at_{Xaxis[i]}.\\n')
    results.write(f'Long-run_values_at_bifurcation:{set(np.round(ydat,_precis))};_
        Value_Count_{len(set(np.round(ydat,_precis)))}.\n')
    results.write(f'Analysis_done_rounding_to_{precis}_decimal_places.\n\\n')

def rbifurana(lower, upper, points, Yaxis, usearch, period, precis):

```

```
last = 30
param = np.linspace(lower, upper, points)
Xaxis = np.repeat(param, last)
bifurfound = False
i = np.nonzero(Xaxis >= usearch)
i = i[0][0]
while bifurfound == False:
    ydat = [Yaxis[i]]
    for j in range(i+1, i+last):
        ydat = np.append(ydat, Yaxis[j])
    count = len(set(np.round(ydat, precis)))
    if count != period:
        print("Bifurcation_Point_Found")
        bifurfound = True
        print("Period_Shift_from")
        print(period)
        print("Bifurcation_Point_at")
        print(Xaxis[i])
        print("Points")
        print(set(np.round(ydat, precis)))
    else:
        i -= last
results.write(f'Bifurcation_Point_found_starting_search_from_{usearch},_right_to_'
             f'left_into_{period}_cycle.\n')
results.write(f'Bifurcation_Point_Found_into_{period}_cycle.\n')
results.write(f'Bifurcation_Point_at_{Xaxis[i]}.')
results.write(f'Long-run_values_at_bifurcation:{set(np.round(ydat,_precis))};_'
             f'Value_Count={len(set(np.round(ydat,_precis)))}.\n')
results.write(f'Analysis_done_rounding_to_{precis}_decimal_places.\n\n')

def sbifurcation(lower, upper, points, dY0, dY1, dY2, dY3, dY4, dY5, k, v, q):
    #Print initial conditions of bifurcation to bifur_results.txt
    results.write(f'Initial_conditions_of_s_bifurcation:_lower={lower},_upper={upper},_'
                 f'points={points},_dY0={dY0},_dY1={dY1},_dY2={dY2},_dY3={dY3},_dY4'
                 f'={dY4},_dY5={dY5},_k={k},_v={v},_q={q}\n\n')
    #Plot set up
```

```
last = 30
iterations = 3000
#Generate distribution of parameter
s = np.linspace(lower, upper, points)
Yaxis = []
#Solve for each parameter value
print("s_Bifurcation")
for j in tqdm(range(points)):
    Income = mapping(dY0, dY1, dY2, dY3, dY4, dY5, s[j], k, v, q, iterations)
    lastvalues = Income[-last:]
    Yaxis.extend(lastvalues)
return(Yaxis)

def kbifurcation(lower, upper, points, dY0, dY1, dY2, dY3, dY4, dY5, s, v, q):
    #Print initial conditions of bifurcation to bifur_results.txt
    results.write(f"Initial_conditions_of_k_bifurcation: lower={lower}, upper={upper},
                  points={points}, dY0={dY0}, dY1={dY1}, dY2={dY2}, dY3={dY3}, dY4
                  ={dY4}, dY5={dY5}, s={s}, v={v}, q={q}\n\n")
    #Plot set up
    last = 30
    iterations = 3000
    #Generate distribution of parameter
    k = np.linspace(lower, upper, points)
    Yaxis = []
    #Solve for each parameter value
    print("k_Bifurcation")
    for j in tqdm(range(points)):
        Income = mapping(dY0, dY1, dY2, dY3, dY4, dY5, s, k[j], v, q, iterations)
        lastvalues = Income[-last:]
        Yaxis.extend(lastvalues)
    return(Yaxis)

def vbifurcation(lower, upper, points, dY0, dY1, dY2, dY3, dY4, dY5, s, k, q):
    #Print initial conditions of bifurcation to bifur_results.txt
    results.write(f"Initial_conditions_of_v_bifurcation: lower={lower}, upper={upper},
                  points={points}, dY0={dY0}, dY1={dY1}, dY2={dY2}, dY3={dY3}, dY4
```

```
={dY4},dY5={dY5},s={s},k={k},q={q}\n\n")
#Plot set up
last = 30
iterations = 3000
#Generate distribution of parameter
v = np.linspace(lower, upper, points)
Yaxis = []
#Solve for each parameter value
print("v_Bifurcation")
for j in tqdm(range(points)):
    Income = mapping(dY0, dY1, dY2, dY3, dY4, dY5, s, k, v[j], q, iterations)
    lastvalues = Income[-last:]
    Yaxis.extend(lastvalues)
return(Yaxis)

def qbifurcation(lower, upper, points, dY0, dY1, dY2, dY3, dY4, dY5, s, k, v):
    #Print initial conditions of bifurcation to bifur_results.txt
    results.write(f'Initial_conditions_of_q_bifurcation: lower={lower},upper={upper},
    points={points},dY0={dY0},dY1={dY1},dY2={dY2},dY3={dY3},dY4
    ={dY4},dY5={dY5},s={s},k={k},v={v}\n\n')
    #Plot set up
    last = 30
    iterations = 3000
    #Generate distribution of parameter
    q = np.linspace(lower, upper, points)
    Yaxis = []
    #Solve for each parameter value
    print("q_Bifurcation")
    for j in tqdm(range(points)):
        Income = mapping(dY0, dY1, dY2, dY3, dY4, dY5, s, k, v, q[j], iterations)
        lastvalues = Income[-last:]
        Yaxis.extend(lastvalues)
    return(Yaxis)

results = open('./computational/metzlerian_growth/bifur-param_results.txt', 'a+')
Yaxis = qbifurcation(0.1, 0.9, 50000, 100, 120, 110, 100, 105, 107, 0.3, 500, 0.001)
```

```
lbifurana(0.65, 0.9, 50000, Yaxis, 0.53, 2, 0)
rbifurana(0.65, 0.9, 50000, Yaxis, 0.53, 2, 0)
Yaxis = kbifurcation(0.1, 0.9, 50000, 100, 120, 110, 100, 105, 107, 0.6, 500, 0.001)
lbifurana(0.1, 0.9, 50000, Yaxis, 0.1, 2, 0)
rbifurana(0.1, 0.9, 50000, Yaxis, 0.9, 2, 0)
Yaxis = vbifurcation(1, 2000, 50000, 100, 120, 110, 100, 105, 107, 0.6, 0.3, 0.001)
lbifurana(1, 2000, 50000, Yaxis, 1, 1, 0)
rbifurana(1, 2000, 50000, Yaxis, 1000, 1, 0)
lbifurana(1, 2000, 50000, Yaxis, 525, 2, 0)
rbifurana(1, 2000, 50000, Yaxis, 525, 2, 0)
Yaxis = qbifurcation(0, 0.002, 50000, 100, 120, 110, 100, 105, 107, 0.6, 0.3, 500)
rbifurana(0, 0.002, 50000, Yaxis, 0.002, 1, 0)
rbifurana(0, 0.002, 50000, Yaxis, 0.001598, 2, 0)
results.close()

import numpy as np
import matplotlib.pyplot as plt
from tqdm import tqdm

#Create growth formula
#Time series with mean of last 3 prediction
def growth(dYt1, dYt2, dYt3, dYt5, dYt6, s, k, v, q):
    dYt = (dYt1 / v) / ((dYt1 / v)**4 + q) - (dYt2 / v) / ((dYt2 / v)**4 + q) +
        ((k+1)/3) * ((1-s)*(dYt2-dYt5)+s*(dYt3-dYt6)) + (1-s)*dYt2 + s*dYt3
    return dY

#Creates mapping for growth model based on growth function
def mapping(dY0, dY1, dY2, dY3, dY4, dY5, s, k, v, q, iter):
    #Initialize vectors
    dY = np.append([dY0, dY1, dY2, dY3, dY4, dY5], np.zeros(iter-6))
    #Simulate
    for t in range(6, iter):
        dY[t] = growth(dY[t-1], dY[t-2], dY[t-3], dY[t-5], dY[t-6], s, k, v, q)
    return dY

def lbifurana(lower, upper, points, Yaxis, lsearch, period, precis):
    last = 30
```

```
param = np.linspace(lower, upper, points)
Xaxis = np.repeat(param, last)
bifurfound = False
i = np.nonzero(Xaxis >= lsearch)
i = i[0][0]
while bifurfound == False:
    ydat = [Yaxis[i]]
    for j in range(i+1, i+last):
        ydat = np.append(ydat, Yaxis[j])
    count = len(set(np.round(ydat, precis)))
    if count != period:
        print("Bifurcation_Point_Found_Searching")
        bifurfound = True
        print("Period_Shift_from")
        print(period)
        print("Bifurcation_Point_at")
        print(Xaxis[i])
        print("Points")
        print(set(np.round(ydat, precis)))
    else:
        i += last
results.write(f'Bifurcation_Point_found_starting_search_from_{lsearch}, left_to_
right_from_{period}_cycle.\n')
results.write(f'Bifurcation_Point_at_{Xaxis[i]}.\\n')
results.write(f'Long-run_values_at_bifurcation:{set(np.round(ydat,precis))};_
Value_Count={len(set(np.round(ydat,precis)))}.\n')
results.write(f'Analysis_done_rounding_to_{precis}_decimal_places.\n\\n')

def rbifurana(lower, upper, points, Yaxis, usearch, period, precis):
    last = 30
    param = np.linspace(lower, upper, points)
    Xaxis = np.repeat(param, last)
    bifurfound = False
    i = np.nonzero(Xaxis >= usearch)
    i = i[0][0]
    while bifurfound == False:
```

```
ydat = [Yaxis[i]]
for j in range(i+1, i+last):
    ydat = np.append(ydat, Yaxis[j])
count = len(set(np.round(ydat, precis)))
if count != period:
    print("Bifurcation_Point_Found")
    bifurfound = True
    print("Period_Shift_from")
    print(period)
    print("Bifurcation_Point_at")
    print(Xaxis[i])
    print("Points")
    print(set(np.round(ydat, precis)))
else:
    i -= last
results.write(f"Bifurcation_Point_found_starting_search_from_{usearch}, right_to_
left_into_{period}_cycle.\n")
results.write(f"Bifurcation_Point_Found_into_{period}_cycle.\n")
results.write(f"Bifurcation_Point_at_{Xaxis[i]}.n")
results.write(f"Long-run_values_at_bifurcation:{set(np.round(ydat,-precis))};_
Value_Count={len(set(np.round(ydat,-precis)))}.\n")
results.write(f"Analysis_done_rounding_to_{precis}_decimal_places.\n\n")

def y0ifurcation(lower, upper, points, dY1, dY2, dY3, dY4, dY5, s, k, v, q):
    #Print initial conditions of bifurcation to bifur_results.txt
    results.write(f"Initial_conditions_of_$.dot_Y_0$.bifurcation:lower={lower},upper
    ={upper},points={points},dY1={dY1},dY2={dY2},dY3={dY3},dY4={
    dY4},dY5={dY5},s={s},k={k},v={v},q={q}\n\n")
    #Plot set up
    last = 30
    iterations = 3000
    #Generate distribution of parameter
    dY0 = np.linspace(lower, upper, points)
    Yaxis = []
    #Solve for each parameter value
    print("s_Bifurcation")
```

```
for j in tqdm(range(points)):
    Income = mapping(dY0[j], dY1, dY2, dY3, dY4, dY5, s, k, v, q, iterations)
    lastvalues = Income[-last:]
    Yaxis.extend(lastvalues)
return(Yaxis)

def y1bifurcation(lower, upper, points, dY0, dY2, dY3, dY4, dY5, s, k, v, q):
    #Print initial conditions of bifurcation to bifur_results.txt
    results.write(f'Initial_conditions_of_{dot}_Y_1$bifurcation: lower={lower}, upper
                  ={upper}, points={points}, dY0={dY0}, dY2={dY2}, dY3={dY3}, dY4={
                  dY4}, dY5={dY5}, s={s}, k={k}, v={v}, q={q}\n\n')
    #Plot set up
    last = 30
    iterations = 3000
    #Generate distribution of parameter
    dY0 = np.linspace(lower, upper, points)
    Yaxis = []
    #Solve for each parameter value
    print("dY1_Bifurcation")
    for j in tqdm(range(points)):
        Income = mapping(dY0, dY1[j], dY2, dY3, dY4, dY5, s, k, v, q, iterations)
        lastvalues = Income[-last:]
        Yaxis.extend(lastvalues)
    return(Yaxis)

def y2ifurcation(lower, upper, points, dY0, dY1, dY3, dY4, dY5, s, k, v, q):
    #Print initial conditions of bifurcation to bifur_results.txt
    results.write(f'Initial_conditions_of_{dot}_Y_2$bifurcation: lower={lower}, upper
                  ={upper}, points={points}, dY0={dY0}, dY1={dY1}, dY3={dY3}, dY4={
                  dY4}, dY5={dY5}, s={s}, k={k}, v={v}, q={q}\n\n')
    #Plot set up
    last = 30
    iterations = 3000
    #Generate distribution of parameter
    dY0 = np.linspace(lower, upper, points)
    Yaxis = []
```

```
#Solve for each parameter value
print("s_Bifurcation")
for j in tqdm(range(points)):
    Income = mapping(dY0, dY1, dY2[j], dY3, dY4, dY5, s, k, v, q, iterations)
    lastvalues = Income[-last:]
    Yaxis.extend(lastvalues)
return(Yaxis)

def y3ifurcation(lower, upper, points, dY0, dY1, dY2, dY4, dY5, s, k, v, q):
    #Print initial conditions of bifurcation to bifur_results.txt
    results.write(f'Initial_conditions_of_{dot}_Y_3_bifurcation: lower={lower}, upper={upper}, points={points}, dY0={dY0}, dY1={dY1}, dY2={dY2}, dY4={dY4}, dY5={dY5}, s={s}, k={k}, v={v}, q={q}\n\n')
    #Plot set up
    last = 30
    iterations = 3000
    #Generate distribution of parameter
    dY0 = np.linspace(lower, upper, points)
    Yaxis = []
    #Solve for each parameter value
    print("s_Bifurcation")
    for j in tqdm(range(points)):
        Income = mapping(dY0, dY1, dY2, dY3[j], dY4, dY5, s, k, v, q, iterations)
        lastvalues = Income[-last:]
        Yaxis.extend(lastvalues)
    return(Yaxis)

def y4ifurcation(lower, upper, points, dY0, dY1, dY2, dY3, dY5, s, k, v, q):
    #Print initial conditions of bifurcation to bifur_results.txt
    results.write(f'Initial_conditions_of_Y_0_bifurcation: lower={lower}, upper={upper}, points={points}, dY0={dY0}, dY1={dY1}, dY2={dY2}, dY3={dY3}, dY5={dY5}, s={s}, k={k}, v={v}, q={q}\n\n')
    #Plot set up
    last = 30
    iterations = 3000
    #Generate distribution of parameter
```

```
dY0 = np.linspace(lower, upper, points)
Yaxis = []
#Solve for each parameter value
print("s_Bifurcation")
for j in tqdm(range(points)):
    Income = mapping(dY0, dY1, dY2, dY3, dY4[j], dY5, s, k, v, q, iterations)
    lastvalues = Income[-last:]
    Yaxis.extend(lastvalues)
return(Yaxis)

def y5bifurcation(lower, upper, points, dY0, dY1, dY2, dY3, dY4, s, k, v, q):
    #Print initial conditions of bifurcation to bifur_results.txt
    results.write(f'Initial_conditions_of_{dY0}_bifurcation: lower={lower}, upper={upper}, points={points}, dY0={dY0}, dY1={dY1}, dY2={dY2}, dY3={dY3}, dY4={dY4}, s={s}, k={k}, v={v}, q={q}\n\n')
    #Plot set up
    last = 30
    iterations = 3000
    #Generate distribution of parameter
    dY0 = np.linspace(lower, upper, points)
    Yaxis = []
    #Solve for each parameter value
    print("s_Bifurcation")
    for j in tqdm(range(points)):
        Income = mapping(dY0, dY1, dY2, dY3, dY4, dY5[j], s, k, v, q, iterations)
        lastvalues = Income[-last:]
        Yaxis.extend(lastvalues)
    return(Yaxis)

results = open('./computational/metzlerian_growth/bifur-init_results.txt', 'a+')
Yaxis = y0bifurcation(-400, 400, 10000, 120, 110, 100, 105, 107, 0.6, 0.3, 500, 0.001)
lbifurana(-400, 400, 10000, Yaxis, -400, 1, 0)
rbifurana(-400, 400, 10000, Yaxis, 0, 2, 0)
lbifurana(-400, 400, 10000, Yaxis, 0, 2, 0)
Yaxis = y1bifurcation(-400, 400, 10000, 100, 110, 100, 105, 107, 0.6, 0.3, 500, 0.001)
lbifurana(-400, 400, 10000, Yaxis, -400, 1, 0)
```

```
rbifurana(-400, 400, 10000, Yaxis, 100, 2, 0)
lbifurana(-400, 400, 10000, Yaxis, 100, 2, 0)
rbifurana(-400, 400, 10000, Yaxis, 400, 2, 0)
ribufrana(-400, 400, 10000, Yaxis, 260, 1, 0)
lbifurana(-400, 400, 10000, Yaxis, 260, 1, 0)
Yaxis = y2bifurcation(-400, 400, 10000, 100, 120, 100, 105, 107, 0.6, 0.3, 500, 0.001)
lbifurana(-400, 400, 10000, Yaxis, -400, 1, 0)
rbifurana(-400, 400, 10000, Yaxis, 100, 2, 0)
lbifurana(-400, 400, 10000, Yaxis, 100, 2, 0)
rbifurana(-400, 400, 10000, Yaxis, 400, 2, 0)
ribufrana(-400, 400, 10000, Yaxis, 260, 1, 0)
lbifurana(-400, 400, 10000, Yaxis, 260, 1, 0)
Yaxis = y3bifurcation(-400, 400, 10000, 100, 120, 110, 105, 107, 0.6, 0.3, 500, 0.001, )
lbifurana(-400, 400, 10000, Yaxis, -400, 1, 0)
rbifurana(-400, 400, 10000, Yaxis, 200, 2, 0)
lbifurana(-400, 400, 10000, Yaxis, 200, 2, 0)
rbifurana(-400, 400, 10000, Yaxis, 400, 1, 0)
Yaxis = y4bifurcation(-400, 400, 10000, 100, 120, 110, 100, 107, 0.6, 0.3, 500, 0.001)
lbifurana(-400, 400, 10000, Yaxis, -400, 1, 0)
rbifurana(-400, 400, 10000, Yaxis, -140, 2, 0)
lbifurana(-400, 400, 10000, Yaxis, -140, 2, 0)
rbifurana(-400, 400, 10000, Yaxis, -20, 2, 0)
lbifurana(-400, 400, 10000, Yaxis, -20, 2, 0)
rbifurana(-400, 400, 10000, Yaxis, 50, 1, 0)
lbifurana(-400, 400, 10000, Yaxis, 50, 1, 0)
rbifurana(-400, 400, 10000, Yaxis, 130, 2, 0)
lbifurana(-400, 400, 10000, Yaxis, -130, 2, 0)
rbifurana(-400, 400, 10000, Yaxis, 400, 1, 0)
Yaxis = y5bifurcation(-400, 400, 10000, 100, 120, 110, 100, 105, 0.6, 0.3, 500, 0.001)
lbifurana(-400, 400, 10000, Yaxis, -400, 1, 0)
rbifurana(-400, 400, 10000, Yaxis, -0, 2, 0)
lbifurana(-400, 400, 10000, Yaxis, -0, 2, 0)
rbifurana(-400, 400, 10000, Yaxis, 120, 2, 0)
rbifurana(-400, 400, 10000, Yaxis, 300, 1, 0)

results.close()
```

D.5 Results of Bifurcation Analysis

Initial conditions of s bifurcation: lower=0.1, upper=0.9, points=50000, dY0=100, dY1=120, dY2=110, dY3=100, dY4=105, dY5=107, k=0.3, v=500, q=0.001

Bifurcation Point found starting search from 0.53, left to right from 2 cycle. Bifurcation Point at 0.65. Long-run values at bifurcation: 131.0, 4.0, 132.0, 6.0, 133.0, 136.0, 135.0, 23.0, 31.0, 34.0, 46.0, 54.0, 67.0, 70.0, 76.0, 95.0, 98.0, 102.0, -19.0, -18.0, 110.0, 112.0, 114.0, -14.0, 118.0, -10.0, 120.0, 122.0, -1.0; Value Count = 29. Analysis done rounding to 0 decimal places.

Bifurcation Point found starting search from 0.53, right to left into 2 cycle. Bifurcation Point Found into 2 cycle. Bifurcation Point at 0.65. Long-run values at bifurcation: 131.0, 4.0, 132.0, 6.0, 133.0, 136.0, 135.0, 23.0, 31.0, 34.0, 46.0, 54.0, 67.0, 70.0, 76.0, 95.0, 98.0, 102.0, -19.0, -18.0, 110.0, 112.0, 114.0, -14.0, 118.0, -10.0, 120.0, 122.0, -1.0; Value Count = 29. Analysis done rounding to 0 decimal places.

Initial conditions of k bifurcation: lower=0.1, upper=0.9, points=50000, dY0=100, dY1=120, dY2=110, dY3=100, dY4=105, dY5=107, s=0.6, v=500, q=0.001

Bifurcation Point found starting search from 0.1, left to right from 2 cycle. Bifurcation Point at 0.8483669673393468. Long-run values at bifurcation: -109.0, -99.0, -96.0, -91.0, 44.0, -83.0, -82.0, -84.0, -80.0, 51.0, -74.0, 55.0, -69.0, 61.0, -67.0, 67.0, -60.0, 73.0, -54.0, 75.0, 78.0, 87.0, -37.0, 91.0, 94.0, 96.0, 97.0, -30.0; Value Count = 28. Analysis done rounding to 0 decimal places.

Bifurcation Point found starting search from 0.9, right to left into 2 cycle. Bifurcation Point Found into 2 cycle. Bifurcation Point at 0.8994559891197824. Long-run values at bifurcation: -207.0, 140.0, -75.0; Value Count = 3. Analysis done rounding to 0 decimal places.

Initial conditions of v bifurcation: lower=1, upper=2000, points=50000, dY0=100, dY1=120, dY2=110, dY3=100, dY4=105, dY5=107, s=0.6, k=0.3, q=0.001

Bifurcation Point found starting search from 1, left to right from 1 cycle. Bifurcation Point at 297.33768675373506. Long-run values at bifurcation: 101.0, 102.0; Value Count = 2. Analysis done rounding to 0 decimal places.

Bifurcation Point found starting search from 1000, right to left into 1 cycle. Bifurcation Point Found into 1 cycle. Bifurcation Point at 617.1041220824416. Long-run values at bifurcation: 101.0, 102.0; Value Count = 2. Analysis done rounding to 0 decimal places.

Bifurcation Point found starting search from 525, left to right from 2 cycle. Bifurcation Point at 589.7572551451028. Long-run values at bifurcation: 74.0, 77.0, 79.0, 85.0, 90.0, 92.0, 94.0, 96.0, 97.0, 99.0, 100.0, 102.0, 104.0, 105.0, 106.0, 108.0, 109.0, 112.0, 113.0,

116.0, 119.0, 121.0, 123.0; Value Count = 23. Analysis done rounding to 0 decimal places.

Bifurcation Point found starting search from 525, right to left into 2 cycle. Bifurcation Point Found into 2 cycle. Bifurcation Point at 472.17372347446945. Long-run values at bifurcation: 226.0, 83.0, -121.0; Value Count = 3. Analysis done rounding to 0 decimal places.

Initial conditions of q bifurcation: lower=0, upper=0.002, points=50000, dY0=100, dY1=120, dY2=110, dY3=100, dY4=105, dY5=107, s=0.6, k=0.3, v=500

Bifurcation Point found starting search from 0.002, right to left into 1 cycle. Bifurcation Point Found into 1 cycle. Bifurcation Point at 0.0015997119942398846. Long-run values at bifurcation: 101.0, 102.0; Value Count = 2. Analysis done rounding to 0 decimal places.

Bifurcation Point found starting search from 0.001598, right to left into 2 cycle. Bifurcation Point Found into 2 cycle. Bifurcation Point at 0.0015976319526390527. Long-run values at bifurcation: 100.0, 101.0, 102.0; Value Count = 3. Analysis done rounding to 0 decimal places.